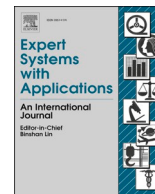




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A novel multi-attribute decision-making for ranking mobile payment services using online consumer reviews

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ABSTRACT

The onset of the COVID-19 pandemic has changed consumer usage behavior towards mobile payment (m-payment) services. Consumer usage behavior towards m-payment services continues to increase due to access to usage experiences shared through online consumer reviews (OCRs). The proliferation of massive OCRs, coupled with quick and effective decisions concerning the evaluation and selection of m-payment services, is a practical issue for research. This paper develops a novel decision evaluation model that integrates OCRs and multi-attribute decision-making (MADM) with probabilistic linguistic information to identify m-payment usage attributes and utilize these attributes to evaluate and rank m-payment services. First and foremost, the attributes of m-payment usage discussed by consumers in OCRs are extracted using the Latent Dirichlet Allocation (LDA) topic modeling approach. These key attributes are used as the evaluation scales in the MADM. Based on an unsupervised sentiment algorithm, the sentiment scores of the text reviews regarding the attributes are calculated. We convert the sentiment scores into probabilistic linguistic elements based on the probabilistic linguistic term set (PLTS) theory and statistical analysis. Furthermore, we construct a novel technique known as probabilistic linguistic indifference threshold-based attribute ratio analysis (PL-ITARA) to discover the weight importance of the usage attributes. Subsequently, the positive and negative ideal-based PL-ELECTRE I methodology is proposed to evaluate and rank m-payment services. Finally, a case study on selecting appropriate m-payment services in Ghana is examined to authenticate the validity and applicability of our proposed decision evaluation methodology.

1. Introduction

In recent times, mobile technologies have revolutionized payment systems. As a result, payment has become one of the most treated topics within economics, technology, finance, and trade. Mobile payment (m-payment) involves utilizing wireless communication and mobile devices to procure goods and services (Shaw et al., 2022). M-payment offers consumers fast, easy, independent, mobility, and agility in transactions (Bojjagani et al., 2021). M-payment holds a substantial benefit for both merchants and consumers. On the one hand, it allows merchants to increase transaction volume because of decreased transaction costs and consumer loyalty. On the other hand, it provides a pleasant purchasing experience with secure, fast, and convenient payment services. Promoting m-payment is very important for economies to achieve financial

inclusion among citizens. M-payment services empower citizens digitally, lessen intermediation, and make society cashless. With the widespread use of smartphones, consumers can quickly transfer money without physical contact between the payer and the payee (Kar, 2021). With the advent of online services, which depend on m-payment services, more entities are becoming related to the m-payment market.

M-payment has seen tremendous growth in the developed world like the USA, Europe, and the Asia-Pacific. It is projected that the m-payment market will be \$4.574 trillion US by 2023 (Allied Market Research, 2018). As a result of the potential opportunities the m-payment market provides, many entities like telecommunication operators, financial institutions, and the information communication technology (ICT) have shifted their attention to offer a host of mobile services such as online ticketing, online shopping, fund transfer and payment of utilities (Kwon

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& Choi, 2022). These mobile services have made life more comfortable for society. Further, when it comes to m-payments, the effects of the COVID-19 pandemic have led to behavioral changes among consumers worldwide. These changes are evident from the USA to Latin America, Africa, and the Middle East (Jones, 2020). These swift changes in consumer behavior provide the impetus for researchers to study contactless payment methods.

Several studies have been conducted on m-payments, but technology adoption has been studied for a long time (Kwon & Choi, 2022). A review undertaken by Dahlberg et al. (2015) on m-payment research revealed three thematic areas: strategy and ecosystem, technology, and adoption. However, the adoption of m-payment has recently caught scholars' attention due to drastic and rapid changes in consumer habits. Numerous theories and models have emerged from different disciplines to thoroughly examine the issue of m-payment adoption. Some of these theories and models include the technology acceptance model (TAM), the innovation diffusion theory (DOI), and the unified theories of acceptance and use of technology (UTAUT). Although the applicability of these models is in tandem with the adoption and continued use of m-payment, they do not fully reflect consumers' usage experience. These models quantify the total experience of service utilization over a period, commonly referred to as user experience (Wixom & Todd, 2005). Therefore, unfortunately, these adoption models do not consider the "usage" experience, which is separate from the "user" experience. Usage experience is linked to a specific instant in analyzing a service encounter (Kar, 2021). Generally, the previous research has assessed the overall consumer experience since measuring usage experience is difficult because consumers cannot be accessed at the point when they consume a service. Characteristically, the previous literature measures overall consumer experience since measuring usage experience is difficult due to access to the consumer at the moment of service consumption. According to the studies of Becker & Jaakkola (2020), examining consumer experience directly after consuming mobile services is scarce in the literature. Handling consumers' usage experience is conceivably the most significant element in creating customer loyalty and continuance usage of m-payment services. With the growth of information systems (Lv et al., 2022), social media (Cao et al., 2021), and artificial intelligence (AI) (Olan et al., 2021), consumers' usage experiences can easily be understood and transformed by service providers. In a nutshell, we identify the following gaps from an extensive review of the literature on mobile service science and m-payment:

- (1) Numerous studies have extensively examined the factors to technology adoption (Choi et al., 2020; Jucevski et al., 2020; Karimi & Liu, 2020; Kumar et al., 2021; Shaw et al., 2022); however, their connection with usage experience is absent.
- (2) The previous studies have established the association between service quality literature and adoption and concluded that sound judgment concerning service quality enhances adoption. Nevertheless, few studies (Kar, 2021; Teng & Khong, 2021) measure mobile service usage experience by integrating these two literature groups, especially by mining online consumer reviews (OCRs).
- (3) The few extant studies (Kar, 2021; Teng & Khong, 2021) that sought to apply OCRs to measure usage experience failed to account for the ambiguity and uncertainty in consumers' sentiments.
- (4) Furthermore, most studies on m-payment adoption failed to provide a straightforward decision-making approach to help consumers evaluate m-payment services and adopt the optimal one.

Conventionally, the public found it difficult to access customers' usage experiences with a brand or service; however, with the proliferation of social media and online review platforms, these experiences can now be retrieved. Consumers can now easily articulate their petitions

and sentiments reflecting their experiences with a brand or service. For instance, online application stores such as Google play store (<https://www.play.google.com>), Apple app store (<https://www.apple.com>), Mobogenie app store (<https://mobogenie.website>), etc., have provided avenues for users to post their feelings and experiences in the form of reviews concerning the usage of services or products. In this information era, potential consumers can learn from the experiences shared by others. Hence, firms need to monitor and analyze how consumers reveal their experiences online, for instance, in OCRs. With the discussion so far, the purpose of this study is to propose an OCRs-driven uncertain evaluation model to examine the factors that influence consumers' usage of m-payment services and to compare and rank m-payment services for better adoption decisions.

OCRs are a promising source of data for m-payment services marketing because they are considered low-cost, easily accessible, and dynamic (Kar, 2021; Teng & Khong, 2021). OCRs aid consumers to make informed decisions about services consumption and, at the same time, help managers improve their services (Shaw et al., 2022). OCRs yield Big Data and produce valuable information, which successfully affects consumer usage decisions (Yu et al., 2020; Zhao et al., 2021). In this information era, potential consumers of m-payment services usually refer to different opinions relating to the performance of m-payment service providers from the existing consumers. Hence, OCRs provide an immediate source of information to measure consumer usage behavior of m-payment services. Meanwhile, OCRs are vague and ambiguous due to the nature of human thinking and feelings (Liang et al., 2021). Therefore, service providers and prospective consumers may find it difficult to obtain meaningful outcomes when using OCRs. Zadeh (1965) proposed a fuzzy set theory to deal with the uncertainty and vagueness in real-world decision-making problems. One fuzzy set concept that has become popular among many scholars is the probabilistic linguistic term set (PLTS) (Pang et al., 2016). Therefore, we utilize the PLTS to model the OCRs to overcome the uncertainty and vagueness. In this instance, the PLTS is optimal since it establishes all possible linguistic terms and their corresponding probabilities (Pang et al., 2016). Liu & Teng (2019) argued that PLTS is an effective instrument to express fuzzy information in MADM problems because it can best preserve the original OCRs. Based on previous studies (Yu et al., 2020; Zhao et al., 2021), it is possible to express the OCRs consumers share about m-payment services in PLTS.

The comparison and ranking of m-payment services can be viewed as a multi-attribute decision-making (MADM) problem. Decision-making techniques are fundamental in the comparison and prioritization of m-payment services. Numerous MADM methods are available (Yalcin et al., 2022); however, the ELECTRE I method proposed by Roy (1968) has received much attention. The ELECTRE I method is an outranking method that relies on pairwise comparisons to rank alternatives. ELECTRE I is used in this paper because it delivers a more realistic decision-making process by considering the attribute importance weight and allows decision-makers to include their preferences into the decision-making process (Agrebi et al., 2017). As an additional consequence, the ELECTRE I considers the violation of the comparability hypothesis (in some cases, a preference or indifference relationship between two alternatives cannot be established) as well as the potential for discrimination (Fattoruso et al., 2019). Singh & Kaushik (2019) investigated intrusion response prioritization based on the fuzzy ELECTRE I MADM technique. Furthermore, Fattoruso et al. (2019) used ELECTRE I to analyze the behavior of economic agents. The previous literature shows that the ELECTRE I method has been applied in various scenarios. However, no work has been done using ELECTRE I-based OCRs to evaluate m-payment services to our best knowledge.

To this end, this paper aims to develop a novel, uncertain evaluation model based on OCRs for comparing m-payment services and identifying the factors affecting consumers' usage decisions. To achieve this goal, we mine OCRs regarding m-payment services' consumption and the succeeding experiences surrounding them. We employ text-mining

techniques like topic modeling and sentiment analysis to analyze the OCRs. These text mining methods extract the key factors that affect usage behavior and subsequent evaluation of m-payment services. Again, we extend the ELECTRE I method into the probabilistic linguistic environment and develop a new evaluation method. The ELECTRE I method is limited because it offers a partial ranking (Çalı & Balaman, 2019). We integrate positive and negative ideal solutions with the ELECTRE I method and develop a new decision-making technique to offer a complete ranking of m-payment services. In this proposed method, the weight importance of key evaluation factors plays a significant role. Hence, we design a new weight determination method to ascertain the importance of the factors impacting the usage of m-payment services. Specifically, we extend the indifference threshold-based attribute ratio analysis (ITARA) (Hatefi, 2019) into the probabilistic environment and develop a probabilistic linguistic indifference threshold-based attribute ratio analysis (PL-ITARA) method. As a result, we contribute to the literature in the following ways:

- (1) The paper makes a valuable input in adoption and service marketing literature by proposing an uncertain evaluation model capable of enhancing the consumer decision-making process of mobile services.
- (2) Employing text mining approaches such as topic modeling and sentiment analysis can aid in the extraction of key attributes influencing m-payment service usage.
- (3) Integrating sentiment analysis and PLTS can solve the uncertainty and imprecision of OCRs, which is missing in m-payment adoption literature.
- (4) Designing a novel weight determination method known as probabilistic linguistic indifference threshold-based attribute ratio analysis (PL-ITARA) can aid in determining the weight importance of key attributes influencing m-payment service usage.
- (5) The development of positive and negative ideal-based PL-ELECTRE I method can provide an approach to evaluate m-payment services.
- (6) The proposed decision-support model is used to investigate a case study of m-payment services in Ghana, which aims to reveal the m-payment usage experience and the evaluation of m-payment services.

Proposing such a comprehension evaluation model can aid service providers and prospective consumers in better-understanding consumer usage decisions on m-payment service. Our proposed model provides an easy and robust approach to assist prospective consumers in selecting m-payment services. Furthermore, service providers using our proposed model will comprehend the performance of their m-payment services on the market. Knowing the performance of m-payment services will enable service providers to strategize and improve these services.

The rest of the paper is introduced as follows: Section 2 explains the literature review on m-payment adoption, OCRs, MADM, and PLTSs. In Section 3, we discuss the proposed decision evaluation methodology. Section 4 describes a case study to test the robustness and applicability of our proposed method. Moreover, a comparative analysis is also included in this section. Meanwhile the theoretical and practical implications of the study is also discussed. Section 5 concludes the findings and provides some limitations and future works.

2. Literature review

This section discusses the literature on m-payment adoption, OCRs, MADM, and the PLTSs theory.

2.1. Adoption of mobile payment

Mobile payment (m-payment) utilizes wireless communication and

mobile devices to procure goods and services (Shaw et al., 2022). Also, m-payment services denote any business activity that employs mobile devices to efficaciously complete trade transactions (Kar, 2021). M-payment can be categorized into two main types: proximity m-payment and remote m-payment (Jocovski et al., 2020), which occur in physical stores and at a distance. M-payment has become a potential for many online businesses, including buying tickets to paying for transportation, and many others.

The growth of m-payment services has been possible through the improvements in technology advancements. The literature has further thrown light on the several dominant adoption theories such as Theory of Reasoned Action (TRA), Technology Acceptance Model (TAM), Theory of Planned Behaviour (TPB), Diffusion of Innovation (DOI), Theory of Interpersonal Behaviour (TIB), Unified Theory of Acceptance and Use of Technology (UTAUT), Model of Adoption of Technology in Households (MATH) and Motivational Model. These models have been utilized to examine the mechanism of consumers' adoption behavior concerning both general and specific technologies such as m-payment. A synopsis of the literature on mobile payments is provided in Table 1.

Studies on mobile payment are steadily increasing, as evidenced by the literature. It's observed that the most employed research model comprises the TAM, UTAUT, and UTAUT2 (Al-Saedi et al., 2020; Cao & Niu, 2019; Chaiyasoonthorn & Suksangiam, 2019; Liébana-Cabanillas et al., 2018; Oliveira et al., 2016; Singh & Sinha, 2020). In addition, most of the extant studies adopted surveys to obtain data. We argue that the traditional survey methods validate scholars' prior expectations on m-payment adoption factors. Moreover, these survey methods fail to measure consumer experience immediately after service consumption. To address this issue, Teng & Khong (2021) used a text mining approach

Table 1
Literature review on m-payment adoption.

Author(s)	Category	Theory/Model	Methods
(T. Oliveira et al., 2016)	Adoption	UTAUT2/DOI	Survey
(Ozturk et al., 2017)	Adoption	Valence theory	Survey
(Iman, 2018)	Ecosystem	Business model analysis	Case study, Interviews
(Johnson et al., 2018)	Adoption	DOI	Survey
(Liébana-Cabanillas et al., 2018)	Adoption	TAM	Survey
(Cao & Niu, 2019)	Adoption	UTAUT	Survey
(Chaiyasoonthorn & Suksangiam, 2019)	Adoption	UTAUT2	Survey
(Chaurasia et al., 2019)	Adoption	Motivational model	Survey
(Webb et al., 2019)	Ecosystem	Sectoral Systems of Innovation	Interviews
(Choi et al., 2020)	Adoption	Mobile payment service evaluations by consumers	Conjoint survey
(Al-Saedi et al., 2020)	Adoption	UTAUT	Survey
(Jocovski et al., 2020)	Ecosystem	Two-sided platform business model	Case study, Interviews
(Karimi & Liu, 2020)	Adoption	Mood valence, Maximization tendency	Scenario-based experiment
(Kaur et al., 2020)	Adoption	Innovation resistance theory	Survey
(Singh & Sinha, 2020)	Adoption	TAM	Survey
(Wang & Lai, 2020)	Adoption	System dynamics and two-sided m-payment platform	Conjoint survey
(Kumar et al., 2021)	Adoption	Network effects and institutional theory	Survey
(Cao, 2021)	Adoption	Determinants of mobile payment services	Survey
(Teng & Khong, 2021)	Adoption/Ecosystem	Text mining	Online reviews
(Shaw et al., 2022)	Adoption	DOI	Survey

to extract the relevant m-payment adoption factors from different social media platforms. Data from social media platforms are usually characterized by uncertainty and fussiness; however, the previous literature on m-payment adoption failed to account for the problem of uncertainty and imprecision. After reviewing the extant studies concerning m-payment adoption, most studies mainly discussed the factors and barriers to adopting m-payment. None of the studies tried to provide a methodological approach through which consumers can leverage the m-payment attributes to evaluate m-payment services. Therefore, this current study closes the literature gap by employing OCRs to measure consumer usage experiences regarding the attributes that impact the usage of m-payment services. In addition, the study proposes an uncertain evaluation model that aids consumers in evaluating and selecting suitable m-payment(s).

2.2. Online reviews and MADM

The upsurge of online media has enabled consumers to actively and regularly share their opinions regarding products or services on online platforms. Online reviews are a great source of information for consumers. The issue of ranking alternatives based on MADM with online reviews is still relatively rare in the current research.

To evaluate products/services concerning the information representation model from the online reviews, many MADM methods have been developed. For instance, Chen et al. (2015) visualize market structures using online product reviews and the TOPSIS method. In addition, Abirami & Askarunisa (2017) investigated customers' level of satisfaction using online reviews, SAW, and TOPSIS methods. Liu & Teng (2019) proposed a probabilistic linguistic TODIM method for selecting products through online product reviews. Zhang et al. (2020) also developed an algorithm to utilize intuitionistic and hesitant fuzzy information to rank products with online reviews. Khan et al. (2021) proposed a decision support model for hotel recommendation using OCRs and logarithmic spherical hesitant fuzzy information. Awajan et al. (2021) employed sentiment analysis technique and neutrosophic set theory for mining and ranking Big Data from OCRs.

The discussion so far reveals that literature on the integration of online reviews and MADM is inadequate, especially in m-payment adoption discussion. Most of the prior studies focused on consumer products and customer satisfaction. Therefore, integrating OCRs and MADM technique as a decision-making framework for analyzing m-payment usage is in the right direction. Moreover, most of these MADM methods rank alternatives using the scoring or prospect models. Also, careful observation reveals that none of the studies which fuse sentiment examination and MADM procedures to evaluate products utilized the ELECTRE I method with probabilistic linguistic information or a hybrid model that combines the strength of distinct methods. Therefore, it is necessary to adopt other models like the compromising methods to evaluate m-payment services according to the information representation model from the OCRs.

2.3. Preliminaries

In this section, we concisely put forward some elementary thoughts of PLTS, which is an advancement of the hesitant fuzzy linguistic term set (HFLTS). Consequently, this section serves as the theoretical basis for the succeeding sections.

Pang et al. (2016) developed the probabilistic linguistic term set to improve the HFLTS. The PLTS can depict the importance of the linguistic terms based on the probabilities associated with them. The PLTS is defined as:

Definition 1. (Pang et al., 2016) Let $l = \{l_\theta | \theta = 0, 1, \dots, \tau\}$ be a linguistic term set. Then, a probabilistic term set (PLTS) is defined as follows:

$$L(p) = \left\{ L^{(k)}(p^{(k)}) | L^{(k)} \in l, r^{(k)} \in \vartheta, p^{(k)} \geq 0, k = 1, 2, \dots, \#L(p), \sum_{k=1}^{\#L(p)} p^{(k)} \leq 1 \right\}, \tag{1}$$

where $L^{(k)}(p^{(k)})$ is the linguistic term $L^{(k)}$ corresponding to the probability $p^{(k)}$, $r^{(k)}$ is the subscript of $L^{(k)}$, and $\#L(p)$ is the number of all linguistic terms in $L(p)$. If all the elements $L^{(k)}(p^{(k)})$ in $L(p)$ are ranked by the values of $r^{(k)}p^{(k)}$ in descending order, then $L(p)$ is called an ordered PLTS.

Definition 2. (Pang et al., 2016) Let $L_1(p_1) = \{L_1^{(k)}(p_1^{(k)}) | k = 1, 2, \dots, \#L_1(p_1)\}$ and $L_2(p_2) = \{L_2^{(k)}(p_2^{(k)}) | k = 1, 2, \dots, \#L_2(p_2)\}$ be any two PLTSs, where $\#L_1(p_1)$ and $\#L_2(p_2)$ are the numbers of linguistic terms in $L_1(p_1)$ and $L_2(p_2)$ respectively. If $\#L_2(p_2) < \#L_1(p_1)$, then $\#L_1(p_1) - \#L_2(p_2)$ linguistic terms are added to $L_2(p_2)$ until the numbers of linguistic terms in $L_1(p_1)$ and $L_2(p_2)$ are equal. The added linguistic terms are the least ones in $L_2(p_2)$, and their corresponding probabilities are zero.

To preserve all linguistic information in the process of information fusion, Bai et al. (2017) introduced a matching transformation function for the PLTSs:

Definition 3. Let $l = \{l_\theta | \theta = -\tau, \dots, -1, 0, 1, \dots, \tau\}$ be a linguistic term set. $L(p)$ is considered as PLTS. Then, the corresponding transformation function of $L(p)$ is defined as follows:

$$g(L(p)) = \left\{ \left[\frac{r^{(k)}}{2\tau} + \frac{1}{2} \right] (p^{(k)}) \right\} = L_\gamma(p), \tag{2}$$

where $g : [-\tau, \tau] \rightarrow [0, 1]$ and $\gamma \in [0, 1]$. Analogously, the conversion function of $L_\gamma(p)$ can be calculated as follows:

$$g^{-1}(L_\gamma(p)) = \{l_{(2\gamma-1)\tau}(p^{(k)}) | \gamma \in [0, 1]\} = L(p), \tag{3}$$

where $g^{-1} : [0, 1] \rightarrow [-\tau, \tau]$.

To compare and rank two PLTSs, Pang et al. (2016) proposed the following score and deviation degree formulae:

Definition 4. Let $L(p) = \{L^{(k)}(p^{(k)}) | k = 1, 2, \dots, \#L(p)\}$ be a PLTS, and $r^{(k)}$ is the subscript of the linguistic term $L^{(k)}$. Then, the score $E(L(p))$ and deviation degree $\sigma(L(p))$ of $L(p)$ is given as follows:

$$E(L(p)) = s_{\bar{a}}, \quad \bar{a} = \frac{\sum_{k=1}^{\#L(p)} r^{(k)} p^{(k)}}{\sum_{k=1}^{\#L(p)} p^{(k)}}, \tag{4}$$

$$\sigma(L(p)) = \frac{\left(\sum_{k=1}^{\#L(p)} (p^{(k)} (r^{(k)} - \bar{a}))^2 \right)^{\frac{1}{2}}}{\sum_{k=1}^{\#L(p)} p^{(k)}}. \tag{5}$$

According to (4) and (5), the ranking method for two PLTSs can be given as (Pang et al., 2016):

- (i) If $E(L_1(p)) > E(L_2(p))$, then $L_1(p)$ is bigger than $L_2(p)$, denoted by $L_1(p) > L_2(p)$;
- (ii) If $E(L_1(p)) = E(L_2(p))$, then
 - (a) if $\sigma(L_1(p)) < \sigma(L_2(p))$, then $L_1(p) > L_2(p)$;
 - (b) if $\sigma(L_1(p)) = \sigma(L_2(p))$, then $L_1(p)$ is indifferent to $L_2(p)$, denoted by $L_1(p) \sim L_2(p)$.

Definition 5. (Mao et al., 2019) Let $L_1(p) = \{L_1^{(k)}(p_1^{(k)}) | k = 1, 2, \dots, \#L_1(p)\}$ and $L_2(p) = \{L_2^{(k)}(p_2^{(k)}) | k = 1, 2, \dots, \#L_2(p)\}$ be two PLTSs with $\#L_1(p) = \#L_2(p)$. Then, the Euclidean distance $d(L_1(p), L_2(p))$ between $L_1(p)$ and $L_2(p)$ is defined as follows:

$$d(L_1(p), L_2(p)) = \sqrt{\frac{\sum_{k=1}^{\#L_1(p)} (p_1^{(k)} g(L_1^{(k)}) - p_2^{(k)} g(L_2^{(k)}))^2}{\#L_1(p)}} \quad (6)$$

3. The proposed decision evaluation model

In this segment, a new evaluation model is designed based on OCRs and MADM to compare and select appropriate m-payment service(s). Firstly, we need to extract and preprocess the OCRs obtained from the related websites. Then, based on the LDA topic modeling approach, the key attributes influencing m-payment usage are mined from the pre-processed text reviews. We conduct sentiment analysis to calculate the sentiment scores of the key attributes using a sentiment analyzer algorithm. According to the sentiment scores of the key attributes with respect to each m-payment service, a PL-decision matrix is constructed based on the PLTS theory. Moreover, a weight determination technique is developed using the ITARA method to assign weights to the key attributes. Then, the study develops the positive and negative ideal-based PL-ELECTRE I method for ranking the m-payment services. The decision-making process of the proposed methodology is portrayed in Fig. 1.

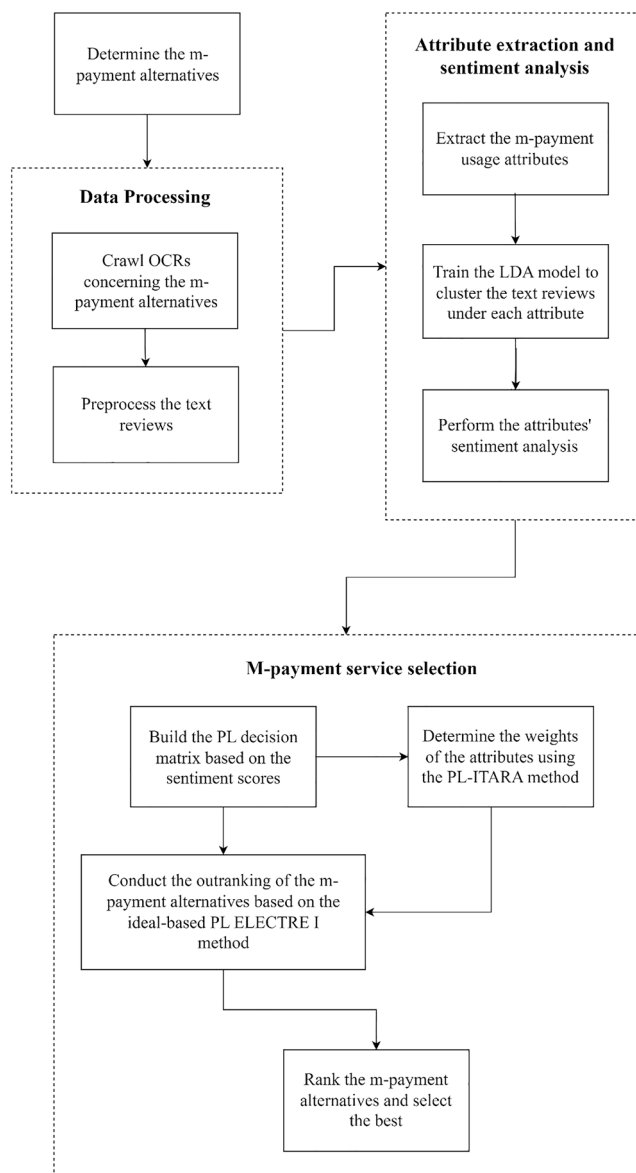


Fig. 1. The proposed decision-making methodology.

3.1. Data Preparation

Data preparation involves two main stages: extracting OCRs and data preprocessing. Natural language processing (NLP) techniques are employed in these steps to accomplish the data preparation phase. A detailed explanation of each step is discussed below.

3.1.1. Crawling OCRs

First and foremost, OCRs concerning m-payment services are crawled from the relevant websites utilizing a python algorithm. Typically, OCRs contain much information such as reviewer name, review date, text reviews, numerical reviews (ratings), etc. Therefore, the required information can be obtained by utilising a python crawler.

3.1.2. Preprocessing the OCRs

At this stage, the study utilizes natural language processing (NLP) methods with python software to preprocess the text reviews for aspect extraction. Text reviews contain thousands of words, of which some may not be relevant in text mining because of the “curse of dimensionality” (Jung & Suh, 2019). Therefore, it is prudent to eliminate immaterial words for improved investigative outcomes. As shown in Fig. 2, the study first cleans the text reviews in the corpus by removing numbers, punctuations, double spacing and converts all the texts into lowercase. Based on the cleaned text reviews, the tokenization of the texts is performed. In this step, the texts are broken down into discrete words. Then, all the English stop words such as “I”, “am”, “what”, “is”, etc., are removed, and lemmatization is carried out to reduce the words into their stem form.

3.2. Aspect extraction and sentiment analysis

To analyze consumers’ sentiments regarding m-payment service usage, we first need to extract the key attributes discussed in the text reviews. We employ the well-known LDA topic modeling approach to extract the key m-payment usage attributes. The outcomes of the trained LDA model include a “Topic-word” matrix and a topic list, where the topic list represents the key attributes extracted. Then, the LDA model is trained to allocate each text review to the various key attributes.

Having obtained the key attributes with their corresponding text reviews; the sentiment scores can be calculated using python software’s unsupervised machine learning algorithm. We apply the VADER sentiment analyzer to obtain the sentiment scores of the reviews concerning the attributes. The sentiment score of each text review is denoted as δ_f , where $\delta_f \in [-1, 1]$. To be precise, -1 denotes the most negative feeling, +1 denotes the highest pleasant mood, and 0 denotes a neutral attitude. The greater the positive/negative value, the more intense the emotion. To provide clarity, Algorithm 1 describes the general sentiment analysis method with VADER.

Algorithm 1 General procedure of sentiment analysis

```

Input: all textual reviews  $Text_f$  and the number of training text  $V$ 
Output: sentiment polarity for each textual review towards each m-payment alternative
for all textual reviews  $Text_f \in [1, V]$  do
  tokenize  $Text_f$  and remove stopwords
end for
for all textual reviews  $Text_f \in [1, V]$  do
  compute the sentiment score  $\delta_f$  with the VADER model
end for
  
```

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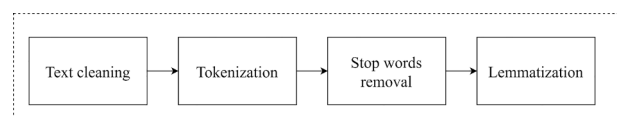


Fig. 2. Overview of the preprocessing approach.

(continued)

Algorithm 1 General procedure of sentiment analysis	
for all m-payment alternatives s_i do	
for all attributes of s_i do	
assign the sentiment score δ_f	
end for	
end for	

3.3. Converting the results of sentiment analysis into PLEs

Usually, text reviews are characterized by vagueness and uncertainties. The paper introduces the PLTS to model the ambiguity and uncertainty in solving real issues of text reviews. Therefore, we can represent the sentiment scores by PLEs. In this scenario, the sentiment scores measure the usage experience of each consumer regarding each m-payment service under each key attribute.

Let $S = \{s_1, s_2, \dots, s_i, \dots, s_m\}$ denote a collection of m-payment services and $A = \{a_1, a_2, \dots, a_j, \dots, a_n\}$ represent a collection of key attributes influencing m-payment usage, $w = (w_1, w_2, \dots, w_n)^T$ indicate the weight information for the attributes, which satisfies the condition that $0 \leq w_j \leq 1$ and $\sum_{j=1}^n w_j = 1$. Then, the usage experience scores of each m-payment service s_i for the key attribute a_j can be discovered according to the following rules (Liu & Teng, 2019):

- (1) Divide the sentiment polarity δ_f , which is between the interval -1 and 1, into five levels:
 - (a) if δ_f is between -1 and -0.5, it can be represented as l_1 (very negative);
 - (b) if δ_f is between -0.5 and 0, it can be described as l_2 (negative);
 - (c) if δ_f is equal to 0, it can be defined as l_3 (neutral);
 - (d) if δ_f is between 0 and 0.5, it can be described as l_4 (positive);
 - (e) if δ_f is between 0.5 and 1, it can be represented as l_5 (very positive);
- (2) Compute the occurrence of each linguistic term and build the PLTS $L_{ij}(p_{ij})$ using the PLTS philosophy and statistical analysis.

Finally, the probabilistic linguistic decision matrix $\Gamma = (\Psi_{ij})_{m \times n}$ in Table 2 can be constructed based on the PLEs obtained for each m-payment service s_i concerning the key attribute a_j .

where Ψ_{ij} represents the usage experience score of the m-payment service s_i concerning the attribute a_j ($i = 1, 2, \dots, m; j = 1, 2, \dots, n$). To preserve the linguistic information in Table 2, we employ Definitions 2 and 3 to normalize and transform the PLEs. Hence, based on Table 2, a transformed ordered normalized decision matrix $\Gamma^T = (\Psi_{ij}^T)_{m \times n}$ is built in Table 3.

where Ψ_{ij}^T represents the transformed ordered normalized usage experience value of the m-payment service s_i concerning the attribute a_j ($i = 1, 2, \dots, m; j = 1, 2, \dots, n$).

Table 2
Probabilistic linguistic decision matrix $\Gamma = (\Psi_{ij})_{m \times n}$.

	a_1	a_2	...	a_j	...	a_n
s_1	$\Psi_{11} = L_{11}(p_{11})$	$\Psi_{12} = L_{12}(p_{12})$...	$\Psi_{1j} = L_{1j}(p_{1j})$...	$\Psi_{1n} = L_{1n}(p_{1n})$
s_2	$\Psi_{21} = L_{21}(p_{21})$	$\Psi_{22} = L_{22}(p_{22})$...	$\Psi_{2j} = L_{2j}(p_{2j})$...	$\Psi_{2n} = L_{2n}(p_{2n})$
\vdots	\vdots	\vdots	...	\vdots	...	\vdots
s_i	$\Psi_{i1} = L_{i1}(p_{i1})$	$\Psi_{i2} = L_{i2}(p_{i2})$...	$\Psi_{ij} = L_{ij}(p_{ij})$...	$\Psi_{in} = L_{in}(p_{in})$
\vdots	\vdots	\vdots	...	\vdots	...	\vdots
s_m	$\Psi_{m1} = L_{m1}(p_{m1})$	$\Psi_{m2} = L_{m2}(p_{m2})$...	$\Psi_{mj} = L_{mj}(p_{mj})$...	$\Psi_{mn} = L_{mn}(p_{mn})$

Table 3
Transformed ordered normalized probabilistic linguistic decision matrix Γ^T .

	a_1	a_2	...	a_j	...	a_n
s_1	$\Psi_{11}^T = g(L_{11}(p_{11}))$	$\Psi_{12}^T = g(L_{12}(p_{12}))$...	$\Psi_{1j}^T = g(L_{1j}(p_{1j}))$...	$\Psi_{1n}^T = g(L_{1n}(p_{1n}))$
s_2	$\Psi_{21}^T = g(L_{21}(p_{21}))$	$\Psi_{22}^T = g(L_{22}(p_{22}))$...	$\Psi_{2j}^T = g(L_{2j}(p_{2j}))$...	$\Psi_{2n}^T = g(L_{2n}(p_{2n}))$
\vdots	\vdots	\vdots	...	\vdots	...	\vdots
s_i	$\Psi_{i1}^T = g(L_{i1}(p_{i1}))$	$\Psi_{i2}^T = g(L_{i2}(p_{i2}))$...	$\Psi_{ij}^T = g(L_{ij}(p_{ij}))$...	$\Psi_{in}^T = g(L_{in}(p_{in}))$
\vdots	\vdots	\vdots	...	\vdots	...	\vdots
s_m	$\Psi_{m1}^T = g(L_{m1}(p_{m1}))$	$\Psi_{m2}^T = g(L_{m2}(p_{m2}))$...	$\Psi_{mj}^T = g(L_{mj}(p_{mj}))$...	$\Psi_{mn}^T = g(L_{mn}(p_{mn}))$

3.4. Determining the weight information

A critical factor in our proposed evaluation model is the importance of the key m-payment usage attributes. Different weights can produce different decision-making results. There are two ways to ascertain the weights of the attributes in the information fusion literature: the subjective and objective methods. We employ the objective weight determination approach in this method. The study extends the ITARA method (Hatefi, 2019) into the probabilistic environment and proposes the PL-ITARA method to estimate the weights of the key m-payment usage attributes.

Firstly, the indifference thresholds ρ_j ($j = 1, 2, \dots, n$) for the attributes ought to be determined. Based on the positive ideal solution, the indifference thresholds ρ_j ($j = 1, 2, \dots, n$) can be ascertained.

Definition 6. Let $\Gamma^T = (\Psi_{ij}^T)_{m \times n}$ be a transformed ordered normalized probabilistic linguistic decision matrix. Then, $\Psi^{T(+)} = (\Psi_1^{T(+)}, \Psi_2^{T(+)}, \dots, \Psi_n^{T(+)})$ is known as the positive ideal solution, where

$$\Psi_j^{T(+)} = \begin{cases} \left(\operatorname{argmax}_{1 \leq i \leq m} E(\Psi_{ij}^T) \right), & \text{for benefit attribute} \\ \left(\operatorname{argmin}_{1 \leq i \leq m} E(\Psi_{ij}^T) \right), & \text{for cost attribute} \end{cases}, \quad (7)$$

It should be emphasized that the values of $\Psi^{T(+)}$ are PLEs and $E(\Psi_{ij}^T)$ are the score function values of Ψ_{ij}^T ($i = 1, 2, \dots, m; j = 1, 2, \dots, n$).

Based on the positive ideal PLE $\Psi_j^{T(+)}$, we calculate the deviation between each m-payment service and the $\Psi_j^{T(+)}$ using (9). Then, we determine the threshold value of each attribute based on the average deviation degree as:

$$\rho_j = \frac{1}{m} \left(\sum_{i=1}^m d(\Psi_{ij}^T, \Psi_j^{T(+)} \right), \quad (8)$$

where m is the number of m-payment services and $d(\Psi_{ij}^T, \Psi_j^{T(+)})$ is computed as follows:

$$d(\Psi_{ij}^T, \Psi_j^{T(+)}) = \sqrt{\frac{\sum_{k=1}^{\#L_{ij}(p)} \left((\rho_{ij}^{(k)} g(L_{ij}^{(k)})) - (\rho_j^{(k)} g(L_j^{(k)}))^+ \right)^2}{\#L_{ij}(p)}} \quad (9)$$

Given the decision matrix $\Gamma^T = (\Psi_{ij}^T)_{m \times n}$, the usage experience values Ψ_{ij}^T must be arranged in ascending order. This can be achieved by utilizing (4) and (5) to compute the scores and the deviation degrees of Ψ_{ij}^T , respectively. Relying on the scores and the deviation degrees, we order the usage experience values Ψ_{ij}^T from the smallest to the largest PLE

in a manner that $\Psi_{ij}^T \leq \Psi_{i+1,j}^T$. Then, an ordered distance $d(\Psi_{ij}^T, \Psi_{i+1,j}^T)$ between the adjacents Ψ_{ij}^T and $\Psi_{i+1,j}^T$ is calculated by using the following formula:

$$d(\Psi_{ij}^T, \Psi_{i+1,j}^T) = \sqrt{\frac{\sum_{k=1}^{\#L_{ij}(p)} (p_{ij}^{(k)} g(L_{ij}^{(k)}) - p_{i+1,j}^{(k)} g(L_{i+1,j}^{(k)}))^2}{\#L_{ij}(p)}} \quad (10)$$

According to $d(\Psi_{ij}^T, \Psi_{i+1,j}^T)$ and ρ_j , the study defines a considerable deviation χ_{ij} as shown in (11).

$$\zeta_{ij} = \begin{cases} d(\Psi_{ij}^T, \Psi_{i+1,j}^T) - \rho_j, & \text{for } d(\Psi_{ij}^T, \Psi_{i+1,j}^T) > \rho_j, \\ 0, & \text{for } d(\Psi_{ij}^T, \Psi_{i+1,j}^T) \leq \rho_j, \end{cases} \quad \forall i \in S, \forall j \in A. \quad (11)$$

For more explanations, if $d(\Psi_{ij}^T, \Psi_{i+1,j}^T) > \rho_j$, then the deviation χ_{ij} should support the weight of the attribute a_j , else this deviation must be discarded (i.e., $\zeta_{ij} = 0$).

An equation for computing the weights of m-payment usage attributes can be formulated based on the l_p – metric measurement. In principle, this measure is an aggregation rule to attain an integrated value across several individual values (Hatefi, 2019). Hence, the formula is given as follows:

$$w_j = \frac{\varpi_j}{\sum_{j=1}^n \varpi_j}, \quad (12)$$

where $\varpi_j = \left(\sum_{i=1}^{m-1} \rho_j^i\right)^{\frac{1}{p}}$, $\forall j \in A$ and p ranges between 1 and ∞ .

3.5. The positive and negative ideal-based PL-ELECTRE I methodology

The study introduces the ELECTRE I into the probabilistic environment to compare m-payment systems and rank them accordingly. The traditional ELECTRE I have a limitation of only ranking the alternatives partially. Therefore, it is essential to integrate it with another method to overcome this limitation. Because of this, the study adopts the positive and negative ideal solutions into the ELECTRE I method to provide complete raking of alternatives. Hence, the positive and negative ideal-based PL-ELECTRE I method is developed to evaluate and rank m-payment services using text reviews as the data source.

3.5.1. Determining the outranking relations of PLEs

In light of Liao et al.'s (2018) study, we employ positive and negative ideal solutions to provide an outranking procedure for PLEs. This outranking procedure serves as a benchmark in comparing the m-payment services. Based on Definition 7, the positive ideal PLEs can be ascertained. Similarly, the definition of the negative ideal PLE can also be given as follows:

Definition 7. Let $\Gamma^T = (\Psi_{ij}^T)_{m \times n}$ be a transformed ordered normalized probabilistic linguistic decision matrix. Then, $\Psi^{T(-)} = (\Psi_1^{T(-)}, \Psi_2^{T(-)}, \dots, \Psi_n^{T(-)})$ is known as the negative ideal solution, where

$$\Psi_j^{T(-)} = \begin{cases} \left(\operatorname{argmin}_{1 \leq i \leq m} E(\Psi_{ij}^T)\right), & \text{for benefit attribute} \\ \left(\operatorname{argmax}_{1 \leq i \leq m} E(\Psi_{ij}^T)\right), & \text{for cost attribute} \end{cases} \quad (13)$$

Based on the positive ideal PLEs and the negative ideal PLEs, the preference for one m-payment service over the other can be computed according to the corresponding attribute.

Given any two m-payment services s_i and s_j , their preference over the attribute a_j can be ascertained by comparing their distance from the positive and the negative ideal PLEs. Firstly, the distance degree $d(\Psi_{ij}^T,$

$\Psi_j^{T(+)})$ and $d(\Psi_{ij}^T, \Psi_j^{T(-)})$ can be computed to identify how far the usage experience Ψ_{ij}^T regarding the m-payment service s_i is away from the positive and negative ideal PLEs, respectively. Similarly, the distance of the m-payment service s_j to the positive and negative ideal PLEs can be denoted as $d(\Psi_{jj}^T, \Psi_j^{T(+)})$ and $d(\Psi_{jj}^T, \Psi_j^{T(-)})$ respectively.

Definition 8. Let Ψ_{ij}^T and $\Psi_j^{T(+)}$ be the usage experience value and the positive ideal PLE with respect to the key attribute a_j , respectively. Then, the distance degree $d(\Psi_{ij}^T, \Psi_j^{T(+)})$ between Ψ_{ij}^T and $\Psi_j^{T(+)}$ is defined as follows:

$$d(\Psi_{ij}^T, \Psi_j^{T(+)}) = \sqrt{\frac{\sum_{k=1}^{\#L(p)} (p_{ij}^{(k)} g(L_{ij}^{(k)}) - p_j^{(k+)} g(L_j^{(k+)})^2}{\#L(p)}}. \quad (14)$$

Definition 9. Let Ψ_{ij}^T and $\Psi_j^{T(-)}$ be the usage experience value and the negative ideal PLE with respect to the key attribute a_j , respectively. Then, the distance degree $d(\Psi_{ij}^T, \Psi_j^{T(-)})$ between Ψ_{ij}^T and $\Psi_j^{T(-)}$ is defined as follows:

$$d(\Psi_{ij}^T, \Psi_j^{T(-)}) = \sqrt{\frac{\sum_{k=1}^{\#L(p)} (p_{ij}^{(k)} g(L_{ij}^{(k)}) - p_j^{(k)-} g(L_j^{(k)-}))^2}{\#L(p)}}. \quad (15)$$

Then, the outranking of two m-payment services can be achieved by comparing the corresponding distance measures. Intuitively, $d(\Psi_{ij}^T, \Psi_j^{T(+)})$ is compared with $d(\Psi_{jj}^T, \Psi_j^{T(+)})$ and $d(\Psi_{ij}^T, \Psi_j^{T(-)})$ with $d(\Psi_{jj}^T, \Psi_j^{T(-)})$, respectively. To scrutinize how “ s_i is strictly preferred to s_j ”, the following three common conditions can be established:

- (1) $d(\Psi_{ij}^T, \Psi_j^{T(+)}) < d(\Psi_{jj}^T, \Psi_j^{T(+)})$ and $d(\Psi_{ij}^T, \Psi_j^{T(-)}) > d(\Psi_{jj}^T, \Psi_j^{T(-)})$;
- (2) $d(\Psi_{ij}^T, \Psi_j^{T(+)}) < d(\Psi_{jj}^T, \Psi_j^{T(+)})$ and $d(\Psi_{ij}^T, \Psi_j^{T(-)}) > d(\Psi_{jj}^T, \Psi_j^{T(-)})$;
- (3) $d(\Psi_{ij}^T, \Psi_j^{T(+)}) = d(\Psi_{jj}^T, \Psi_j^{T(+)})$ and $d(\Psi_{ij}^T, \Psi_j^{T(-)}) > d(\Psi_{jj}^T, \Psi_j^{T(-)})$;
- (4) $d(\Psi_{ij}^T, \Psi_j^{T(+)}) = d(\Psi_{jj}^T, \Psi_j^{T(+)})$ and $d(\Psi_{ij}^T, \Psi_j^{T(-)}) = d(\Psi_{jj}^T, \Psi_j^{T(-)})$.

Also, another unusual situation where s_i may still outrank s_j should not be excluded.

- (5) (a) $d(\Psi_{ij}^T, \Psi_j^{T(+)}) < d(\Psi_{jj}^T, \Psi_j^{T(+)})$ and $d(\Psi_{ij}^T, \Psi_j^{T(-)}) < d(\Psi_{jj}^T, \Psi_j^{T(-)})$
- or
- (b) $d(\Psi_{ij}^T, \Psi_j^{T(+)}) > d(\Psi_{jj}^T, \Psi_j^{T(+)})$ and $d(\Psi_{ij}^T, \Psi_j^{T(-)}) > d(\Psi_{jj}^T, \Psi_j^{T(-)})$.

Based on condition (4), the outranking relationship between s_i and s_j cannot be determined directly. Therefore, the study adopts the relative distance concept $\bar{d} = \frac{d}{d^+ + d^-}$ in the traditional TOPSIS method to investigate further. Let the relative dominance for s_i and s_j be given as

$$\bar{d}_j(\psi_{ij}) = \frac{d(\Psi_{ij}^T, \Psi_j^{T(-)})}{d(\Psi_{ij}^T, \Psi_j^{T(-)}) + d(\Psi_{ij}^T, \Psi_j^{T(+)})} \quad \text{and} \quad \bar{d}_j(\psi_{jj}) = \frac{d(\Psi_{jj}^T, \Psi_j^{T(-)})}{d(\Psi_{jj}^T, \Psi_j^{T(-)}) + d(\Psi_{jj}^T, \Psi_j^{T(+)})}$$

respectively. Suppose that $\bar{d}_j(\psi_{ij}) > \bar{d}_j(\psi_{jj})$, then, the m-payment service s_i is relatively preferred to s_j on the attribute a_j .

Let $\Delta = \{j | j = 1, 2, \dots, n\}$ be the set of subscripts of all the key attributes. With all the circumstances considered above, the concordance set for any two m-payment services s_i and s_j can be categorized into three groups as follows:

- (1) The strong concordance set:

$$\Delta_{ij}^{+S} = \{j | d(\Psi_{ij}^T, \Psi_j^{T(+)}) < d(\Psi_{jj}^T, \Psi_j^{T(+)}) \text{ and } d(\Psi_{ij}^T, \Psi_j^{T(-)}) > d(\Psi_{jj}^T, \Psi_j^{T(-)})\}. \quad (16)$$

- (2) The medium concordance set:

$$\Delta_{if}^{+M} = \left\{ \begin{array}{l} j | \left(d(\Psi_{ij}^T, \Psi_j^{T(+)}), \langle d(\Psi_{if}^T, \Psi_j^{T(+)}), \Psi_j^{T(+)} \rangle \right) \text{ and } d(\Psi_{ij}^T, \Psi_j^{T(-)}) = d(\Psi_{if}^T, \Psi_j^{T(-)}) \text{ or } \\ \left(d(\Psi_{ij}^T, \Psi_j^{T(+)}), \langle d(\Psi_{if}^T, \Psi_j^{T(+)}), \Psi_j^{T(+)} \rangle \right) \text{ and } d(\Psi_{ij}^T, \Psi_j^{T(-)}) \langle d(\Psi_{if}^T, \Psi_j^{T(-)}) \rangle \end{array} \right\} \quad (17)$$

(3) The weak concordance set:

$$\Delta_{if}^{+W} = \{j | \bar{d}(\psi_{ij}) > \bar{d}(\psi_{if})\}. \quad (18)$$

In a similar vein, the discordance set can be subdivided into the following types:

(1) The strong discordance set:

$$\Delta_{if}^{-S} = \left\{ j | d(\Psi_{ij}^T, \Psi_j^{T(+)}), \langle d(\Psi_{if}^T, \Psi_j^{T(+)}), \Psi_j^{T(+)} \rangle \text{ and } d(\Psi_{ij}^T, \Psi_j^{T(-)}) \langle d(\Psi_{if}^T, \Psi_j^{T(-)}) \rangle \right\}. \quad (19)$$

(2) The medium discordance set:

$$\Delta_{if}^{-M} = \left\{ \begin{array}{l} j | \left(d(\Psi_{ij}^T, \Psi_j^{T(+)}), \langle d(\Psi_{if}^T, \Psi_j^{T(+)}), \Psi_j^{T(+)} \rangle \right) \text{ and } d(\Psi_{ij}^T, \Psi_j^{T(-)}) = d(\Psi_{if}^T, \Psi_j^{T(-)}) \text{ or } \\ \left(d(\Psi_{ij}^T, \Psi_j^{T(+)}), \langle d(\Psi_{if}^T, \Psi_j^{T(+)}), \Psi_j^{T(+)} \rangle \right) \text{ and } d(\Psi_{ij}^T, \Psi_j^{T(-)}) \langle d(\Psi_{if}^T, \Psi_j^{T(-)}) \rangle \end{array} \right\}. \quad (20)$$

(3) The weak concordance set:

$$\Delta_{if}^{-W} = \{j | \bar{d}(\psi_{ij}) < \bar{d}(\psi_{if})\}. \quad (21)$$

Also, an indifference set can be obtained as follows:

$$\begin{aligned} \Delta_{if}^I &= \left\{ j | d(\Psi_{ij}^T, \Psi_j^{T(+)}), \langle d(\Psi_{if}^T, \Psi_j^{T(+)}), \Psi_j^{T(+)} \rangle \text{ and } d(\Psi_{ij}^T, \Psi_j^{T(-)}) \right. \\ &= \left. d(\Psi_{if}^T, \Psi_j^{T(-)}) \right\}. \end{aligned} \quad (22)$$

3.5.2. Establishing the concordance and the discordance matrices

Per the sets obtained above, the study describes a concordance index c_{if} between the m-payment services s_i and s_f . Hence, a concordance matrix $C = (c_{if})_{m \times m}$ is constructed as follows:

$$C = \begin{pmatrix} - & c_{12} & \dots & \dots & c_{1m} \\ c_{21} & - & c_{23} & \dots & c_{2m} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ c_{(m-1)1} & \dots & \dots & - & c_{(m-1)m} \\ c_{m1} & c_{m2} & \dots & c_{m(m-1)} & - \end{pmatrix},$$

where

$$\begin{aligned} c_{if} &= \sum_{j \in \Delta_{if}^{+S}} w_j d(\Psi_{ij}^T, \Psi_j^T) + \sum_{j \in \Delta_{if}^{+M}} w_j d(\Psi_{ij}^T, \Psi_j^T) + \sum_{j \in \Delta_{if}^{+W}} w_j d(\Psi_{ij}^T, \Psi_j^T) \\ &+ \sum_{j \in \Delta_{if}^I} w_j d(\Psi_{ij}^T, \Psi_j^T) \end{aligned} \quad (23)$$

Analogously, a discordance index d_{if} between s_i and s_f is defined, and a discordance matrix $D = (d_{if})_{m \times m}$ is built as follows:

$$D = \begin{pmatrix} - & d_{12} & \dots & \dots & d_{1m} \\ d_{21} & - & d_{23} & \dots & d_{2m} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ d_{(m-1)1} & \dots & \dots & - & d_{(m-1)m} \\ d_{m1} & d_{m2} & \dots & d_{m(m-1)} & - \end{pmatrix},$$

where

$$d_{if} = \frac{\max_{j \in \Delta_{if}^{-S} \cup \Delta_{if}^{-M} \cup \Delta_{if}^{-W}} \{w_j d(\Psi_{ij}^T, \Psi_j^T)\}}{\max_{j \in \Delta} w_j d(\Psi_{ij}^T, \Psi_j^T)}. \quad (24)$$

3.5.3. Ranking the m-payment services

The study integrates the concordance and the discordance matrix based on the positive and negative ideal solutions. The fundamental ideology of the positive ideal solution (PIS) and the negative ideal solution (NIS) is that the most optimal m-payment service should be nearer to the PIS and farther away from the NIS. Therefore, a concordance dominance matrix $CD = (cd_{if})_{m \times m}$ and a discordance dominance matrix $DD = (dd_{if})_{m \times m}$ are constructed using the Euclidean distance as follows:

$$cd_{if} = \sqrt{(c_{if} - c^*)^2}, \quad (25)$$

$$dd_{if} = \sqrt{(d_{if} - d^*)^2}, \quad (26)$$

where $c^* = \max_{f=1}^m \left(\max_{i=1}^m \{c_{if}\} \right)$ and $d^* = \max_{f=1}^m \left(\max_{i=1}^m \{d_{if}\} \right)$. On the one hand, the smaller the concordance dominance index cd_{if} , the better the m-payment service s_i . On the other hand, the larger the discordance dominance index dd_{if} , the better the m-payment service s_i . Hence, the study proposes an aggregate dominance matrix R as follows:

$$R = \begin{pmatrix} - & r_{12} & \dots & \dots & r_{1m} \\ r_{21} & - & r_{23} & \dots & r_{2m} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ r_{(m-1)1} & \dots & \dots & - & r_{(m-1)m} \\ r_{m1} & r_{m2} & \dots & r_{m(m-1)} & - \end{pmatrix},$$

where

$$r_{if} = \frac{dd_{if}}{cd_{if} + dd_{if}}, \quad (27)$$

where $0 \leq r_{if} \leq 1$ ($i, f = 1, 2, \dots, m; i \neq f$). It is noted that the larger the aggregate dominance index r_{if} , the more the m-payment service s_i is

preferred to s_j . To select the most preferred m-payment service, the rank index Φ_i ($i = 1, 2, \dots, m$) is defined as follows:

$$\Phi_i = \frac{\sum_{j=1}^{m-1} r_{ij} - \min_{i=1}^m \left[\sum_{j=1}^{m-1} r_{ij} \right]}{\max_{i=1}^m \left[\sum_{j=1}^{m-1} r_{ij} \right] - \min_{i=1}^m \left[\sum_{j=1}^{m-1} r_{ij} \right]} \quad (28)$$

Therefore, the m-payment services are ranked in a descending order of Φ_i ($i = 1, 2, \dots, m$). The m-payment service with the highest Φ_i is the most preferred.

3.5.4. The decision-making algorithm

Given the above-discussed results, a new decision-making algorithm is devised to evaluate and select m-payment services. The main steps are outlined as follows:

Step 1. Extract the key attributes influencing the usage of m-payment services from the text reviews shared by consumers on the related websites using the LDA topic modeling technique.

Step 2. Perform a sentiment analysis based on Algorithm 1 and record the sentiment scores of the text reviews concerning the m-payment attributes.

Step 3. Construct the probability linguistic decision matrix according to the PLTS theory. The probabilistic linguistic information obtained constitutes the comprehensive decision matrix $\Gamma = (\Psi_{ij})_{m \times n}$.

Step 4. Normalize the comprehensive probabilistic linguistic decision matrix $\Gamma = (\Psi_{ij})_{m \times n}$ based on Definition 3 to make the length of the linguistic terms equal. Then, the normalized linguistic terms are arranged in descending order.

Step 5. Transform the ordered normalized probabilistic linguistic decision matrix based on (2) and denote it $\Gamma^T = (\Psi_{ij}^T)_{m \times n}$.

Step 6. Obtain the weight information of the m-payment usage attributes based on the PL-ITARA method and (7)-(12)

Step 7. Determine the outranking relations by constructing different types of concordance and discordance sets using the outranking rules (16)-(22)

Step 8. Establish the concordance matrix $C = (c_{ij})_{m \times m}$ and the discordance matrix $D = (d_{ij})_{m \times m}$ using (23) and (24).

Step 9. Construct the concordance dominance matrix $CD = (cd_{ij})_{m \times m}$ and the discordance dominance matrix $DD = (dd_{ij})_{m \times m}$ using (25) and (26).

Step 10. Compute the aggregate dominance matrix $R = (r_{ij})_{m \times m}$ based on (27).

Step 11. Compute the dominant index Φ_i for each m-payment service by employing (28). Then, the m-payment services are ranked according to the descending order of Φ_i . The larger Φ_i , the better the m-payment service s_i .

4. Case study of m-payment evaluation in Ghana

The improvement of disruptive technologies has made mobile devices attain new functionalities aiding several mobile financial services, such as account transfers, bill payments, person-to-person transfers, proximity payments, remote payments, and other kinds of services (Darko & Liang, 2020). Among the various mobile technologies offered today, m-payment is experiencing exponential growth. The advent of the COVID-19 pandemic has changed the usage behavior of consumers regarding m-payment services in Ghana (Tuffour et al., 2021). For this, several service providers have developed different m-payments for transacting businesses. To acquire feedback from consumers, service providers provide platforms where consumers can share their usage experiences immediately after the service consumption. Mostly, potential consumers rely on these substantial online reviews provided by experienced consumers to inform their usage decisions (Zhang et al., 2019). However, online reviews are voluminous, and it will be difficult for potential consumers to scroll through one by one before deciding on

Table 4
Probabilistic linguistic evaluation decision matrix.

Alternatives	a_1	a_2	a_3	a_4
s_1	{ s_1 (0.032), s_2 (0.053), s_3 (0.116), s_4 (0.358), s_5 (0.442)}	{ s_1 (0.036), s_2 (0.071), s_3 (0.214), s_4 (0.464), s_5 (0.214)}	{ s_1 (0.016), s_2 (0.066), s_3 (0.230), s_4 (0.377), s_5 (0.311)}	{ s_1 (0.018), s_2 (0.091), s_3 (0.182), s_4 (0.200), s_5 (0.509)}
s_2	{ s_1 (0.026), s_2 (0.039), s_3 (0.143), s_4 (0.351), s_5 (0.442)}	{ s_1 (0.028), s_2 (0.083), s_3 (0.222), s_4 (0.417), s_5 (0.250)}	{ s_1 (0.023), s_2 (0.115), s_3 (0.264), s_4 (0.287), s_5 (0.310)}	{ s_2 (0.088), s_3 (0.176), s_4 (0.382), s_5 (0.353)}
s_3	{ s_1 (0.026), s_2 (0.039), s_3 (0.143), s_4 (0.299), s_5 (0.494)}	{ s_2 (0.238), s_3 (0.143), s_4 (0.286), s_5 (0.333)}	{ s_1 (0.029), s_2 (0.130), s_3 (0.290), s_4 (0.159), s_5 (0.391)}	{ s_2 (0.048), s_3 (0.048), s_4 (0.214), s_5 (0.690)}
	a_5	a_6	a_7	a_8
s_1	{ s_2 (0.273), s_3 (0.136), s_4 (0.409), s_5 (0.182)}	{ s_2 (0.209), s_3 (0.233), s_4 (0.302), s_5 (0.256)}	{ s_2 (0.111), s_3 (0.167), s_4 (0.500), s_5 (0.222)}	{ s_1 (0.012), s_2 (0.073), s_3 (0.049), s_4 (0.439), s_5 (0.427)}
s_2	{ s_1 (0.077), s_2 (0.269), s_3 (0.308), s_4 (0.231), s_5 (0.115)}	{ s_2 (0.194), s_3 (0.290), s_4 (0.323), s_5 (0.194)}	{ s_3 (0.081), s_4 (0.486), s_5 (0.432)}	{ s_1 (0.012), s_2 (0.047), s_3 (0.118), s_4 (0.329), s_5 (0.494)}
s_3	{ s_1 (0.054), s_2 (0.189), s_3 (0.324), s_4 (0.189), s_5 (0.243)}	{ s_1 (0.067), s_2 (0.067), s_3 (0.133), s_4 (0.333), s_5 (0.400)}	{ s_1 (0.053), s_2 (0.105), s_3 (0.105), s_4 (0.421), s_5 (0.316)}	{ s_1 (0.012), s_2 (0.035), s_3 (0.106), s_4 (0.318), s_5 (0.529)}

a particular m-payment service. Therefore, based on the proposed positive and negative ideal-based PL-ELECTRE I evaluation model, a potential consumer can understand the attributes that influence m-payment usage and use these attributes for choice decision making.

Regarding this problem of m-payment service selection, three popular m-payment services in the Ghanaian market are identified, i.e.,

- s_1 : Expresspay m-payment
- s_2 : Hubtel m-payment
- s_3 : Slydepay m-payment

Using a python software crawler, the corresponding reviews of these m-payment services are extracted from the google play store (<https://www.play.google.com>). The number of text reviews crawled for each m-payment service is 420, 576, and 544. The text reviews are preprocessed, and by employing the LDA topic model, the m-payment usage attributes discussed in the online reviews are extracted. As a result, eight (8) key m-payment usage attributes are extracted to evaluate the m-payment systems. The eight key attributes include the following: (1) interface complexity (a_1); (2) system update (a_2); (3) verification (a_3); (4) customer support (a_4); (5) system functionality (a_5); (6) service features (a_6); (7) account registration (a_7) and (8) security (a_8). By conducting a sentiment analysis, we obtain the sentiment scores of the text reviews

Table 5
The weight and importance of the m-payment service usage attributes

Attributes	Weight	Importance
Interface complexity (a_1)	0.0394	8 th
System update (a_2)	0.1431	4 th
Verification (a_3)	0.1074	5 th
Customer support (a_4)	0.0588	7 th
System functionality (a_5)	0.2630	1 st
Service features (a_6)	0.0693	6 th
Account registration (a_7)	0.1495	3 rd
Security (a_8)	0.1694	2 nd

Table 6
Distances to the positive and negative ideal PLEs.

	s_1	s_2	s_3
a_1	0.0349,0.0000	0.0313,0.0111	0.0000,0.0349
a_2	0.0254,0.0524	0.0000,0.0329	0.0329,0.0000
a_3	0.0000,0.0944	0.0944,0.0000	0.0849,0.0490
a_4	0.0953,0.1013	0.1719,0.0000	0.0000,0.1719
a_5	0.0058,0.0939	0.0913,0.0000	0.0000,0.0913
a_6	0.0000,0.0243	0.0243,0.0000	0.0000,0.0243
a_7	0.1049,0.0000	0.0000,0.1049	0.1049,0.0000
a_8	0.0594,0.0000	0.0000,0.0594	0.0594,0.0000

under each attribute. Then, according to the rules discussed in Subsection 4.3, we convert the sentiment scores into PLEs and construct a comprehensive probabilistic linguistic decision matrix for the three m-payment services according to the eight key attributes. The decision matrix $\Gamma = (\Psi_{ij})_{3 \times 8}$ is shown in Table 4.

4.1. Decision analysis

We unravel the issue of m-payment selection by employing the positive and negative ideal-based PL-ELECTRE I methodology described in Section 4. The initial decision matrix $\Gamma = (\Psi_{ij})_{3 \times 8}$ is presented in Table 4. The entries in Table 4 are normalized and transformed according to Definitions 2 and 3.

4.1.1. Importance of the m-payment service usage attributes

In light of the transformed ordered normalized linguistic terms, the weights of the m-payment service usage attributes are ascertained using the PL-ITARA method and (7)-(11). The result is presented in Table 5.

The result reveals that system functionality (a_5) with a weight of 0.2630 is the most significant factor influencing the usage of m-payment in the study area. Here, functionality can be defined as the quality of the m-payment system, which relates to the system’s overall performance. Performance is primarily used to quantify how consumers feel after m-payment usage. Performance can be related to the risk, speed, and network usage of m-payments. Evidence on m-payment adoption (Flavian et al., 2020; Slade et al., 2015) asserts that the performance of m-payment systems has a more significant impact on the usage behavior of consumers. The second important factor influencing m-payment usage is the security (a_8), with a weight of 0.1694. In this digital age, security is a significant factor in sustaining the relationship between merchants, users, and payment systems (Dahlberg et al., 2008). A prior study (Kang, 2018) suggests that if consumers perceive that their private information is accessed and used in a manner that raises concern, there will be little incentive to the usage of m-payment. The outcome is consistent with the notion that security impacts the usage behavior of consumers (Khalilzadeh et al., 2017; Singh & Sinha, 2020). The third factor influencing m-payment usage is account registration (a_7), which has a weight of 0.1495. Account registration relates to the easiness with which consumers can sign up for m-payment. If consumers encounter difficulty registering for m-payment services, they will be discouraged from using the system. An extant study (Khalilzadeh et al., 2017) confirms that

Table 7
Concordance and discordance set.

Strong concordance set	Weak concordance set	Indifferent set	Strong discordance set	Weak discordance set
$\Delta_{12}^+ = \{3, 4, 5, 6\}$	$\Delta_{12}^+ = \{\emptyset\}$	$\Delta_{12}^+ = \{\emptyset\}$	$\Delta_{12}^- = \{1, 7, 8\}$	$\Delta_{12}^- = \{2\}$
$\Delta_{13}^+ = \{2, 3\}$	$\Delta_{13}^+ = \{5\}$	$\Delta_{13}^+ = \{6, 7, 8\}$	$\Delta_{13}^- = \{1, 4\}$	$\Delta_{13}^- = \{\emptyset\}$
$\Delta_{21}^+ = \{1, 7, 8\}$	$\Delta_{21}^+ = \{2\}$	$\Delta_{21}^+ = \{\emptyset\}$	$\Delta_{21}^- = \{3, 4, 5, 6\}$	$\Delta_{21}^- = \{\emptyset\}$
$\Delta_{23}^+ = \{2, 7, 8\}$	$\Delta_{23}^+ = \{\emptyset\}$	$\Delta_{23}^+ = \{\emptyset\}$	$\Delta_{23}^- = \{1, 3, 4, 5, 6\}$	$\Delta_{23}^- = \{\emptyset\}$
$\Delta_{31}^+ = \{1, 4\}$	$\Delta_{31}^+ = \{\emptyset\}$	$\Delta_{31}^+ = \{6, 7, 8\}$	$\Delta_{31}^- = \{2, 3\}$	$\Delta_{31}^- = \{5\}$
$\Delta_{32}^+ = \{1, 3, 4, 5, 6\}$	$\Delta_{32}^+ = \{\emptyset\}$	$\Delta_{32}^+ = \{\emptyset\}$	$\Delta_{32}^- = \{2, 7, 8\}$	$\Delta_{32}^- = \{\emptyset\}$

service providers should make it convenient for consumers to register and create accounts without obstacles. Respectively, system update (a_2) (0.1431), authentication (a_3) (0.1074), service features (a_6) (0.0693), customer support (a_4) (0.0588), and interface complexity (a_1) (0.0394) are ranked as fourth, fifth, sixth, seventh and eighth attributes promoting consumer usage behavior of m-payment.

4.1.1.1. Evaluation and ranking of m-payment services. In what follows, we determine the concordance and the discordance sets. According to Definitions 6 and 7, we select the positive and negative ideal PLEs and compute their distances to the PLEs under each attribute using (14) and (15). The outcome is listed in Table 6. Then, we derive the concordance and the discordance sets based on the outranking relations of (16)-(22). The outcome is given in Table 7.

With respect to (23) and (24), we establish the concordance matrix $C = (c_{if})_{m \times m}$ and the discordance dominance matrix $D = (d_{if})_{m \times m}$, respectively, as follows:

$$C = \begin{bmatrix} - & 0.0425 & 0.0181 \\ 0.0298 & - & 0.0317 \\ 0.0070 & 0.0423 & - \end{bmatrix},$$

$$D = \begin{bmatrix} - & 0.6353 & 0.6144 \\ 1.0000 & - & 1.0000 \\ 1.0000 & 0.6532 & - \end{bmatrix}.$$

According to (25) and (26), the concordance dominance matrix $CD = (cd_{if})_{3 \times 3}$ and the discordance dominance matrix $DD = (dd_{if})_{3 \times 3}$ are computed respectively and shown as follows:

$$CD = \begin{bmatrix} - & 0 & 0.0243 \\ 0.0126 & - & 0.0108 \\ 0.0355 & 0.0002 & - \end{bmatrix},$$

$$DD = \begin{bmatrix} - & 0.3647 & 0.3856 \\ 0.0000 & - & 0.000 \\ 0.0000 & 0.3468 & - \end{bmatrix}.$$

Hence, we can obtain the aggregate dominance matrix R_{if} between the m-payment services by employing (27). The obtained outcome is depicted as follows:

$$R_{if} = \begin{bmatrix} - & 1.000 & 0.9406 \\ 0.0000 & - & 0.000 \\ 0.0000 & 0.9995 & - \end{bmatrix}.$$

Given R_{if} and (28), we calculate the dominant index Φ_i ($i = 1, 2, 3$) for each m-payment service and rank them accordingly. The calculated result for each m-payment service is shown as follows:

$$\Phi_1 = 1.0000, \Phi_2 = 0.0000, \Phi_3 = 0.5150.$$

Based on this Φ_i ($i = 1, 2, 3$), the ranking order of the m-payment service is generated as $s_1 \succ s_3 \succ s_2$. Therefore, the most preferred m-payment service is s_1 (Expresspay).

Table 8
Ranking results of the m-payment services by different methods.

No.	Method	Rankings
1	PLWA (Pang et al., 2016)	$s_1 \succ s_2 \succ s_3$
2	PL-TOPSIS (Pang et al., 2016)	$s_1 \succ s_3 \succ s_2$
3	PL-EDAS	$s_3 \succ s_1 \succ s_2$
4	Proposed method	$s_1 \succ s_3 \succ s_2$

4.2. Comparative analysis

We conduct a comparative study in the following sequel to distinguish our proposed method from other PL-MADM methods. Under the probabilistic linguistic environment, many PL-MADM methods have been developed. Considering the same problem of m-payment selection, we use the PLWA (Pang et al., 2016), the PL-TOPSIS (Pang et al., 2016) and the PL-EDAS (Wei et al., 2021) to rank the m-payment services. The outcomes of these methods are compared with our proposed method. The decision results of the different techniques are shown in Table 8.

According to the results of Table 8, the PL-MADM methods produce different rankings. Methods 1 and 2 successfully rank s_1 as the optimal m-payment service, while method 3 ranks s_3 as the optimal candidate. Since our proposed method can select a similar best m-payment service with most PL-MADM methods, we can conclude that our approach is valid and reasonable. The slight differences in the ranking results are attributed to the fact that the proposed method does not directly use the positive ideal and negative ideal solutions to rank the m-payment services, but rather it utilizes concordance and discordance indices to examine the outranking relations among them. This enables decision-makers to compare the performance of each m-payment service under each attribute. The more detailed the outcomes are, the more the decision-maker can have in-depth knowledge about the performance of the m-payment services. The proposed method ensures that the nominated m-payment service performs exceptionally in total and circumvents the bad performance regarding each attribute.

Motivated by the similarity tests performed by Ren et al. (2017) and Chiclana et al. (2013), we compare the similarity of our method with the existing ones. Based on our comparison problem, we hypothesize that:

H_0 : The difference between each pair of ranking results of the existing methods and our proposed methods follows a symmetric distribution around 0.

H_1 : The difference between each pair of ranking results of the existing methods and our proposed methods does not follow a symmetric distribution around 0.

According to the results of Table 8, we employ the Wilcoxon signed-rank test to check the similarity between two different methods. The p -values of the tests are presented in Table 9.

The results of Table 9 indicate that all the p -values are larger than 0.05. The statistics reveal that we should accept H_0 , i.e., these four PL-MADM methods do not have significant differences in the final results. This finding suggests that our proposed method has certain feasibility.

Moreover, we compare our ranking results with the Google Play store (<https://play.google.com/store>). The Google Play store provides star ratings for the m-payment service apps based on consumer satisfaction. The rating system generates performance scores ranging from 1 to 5,

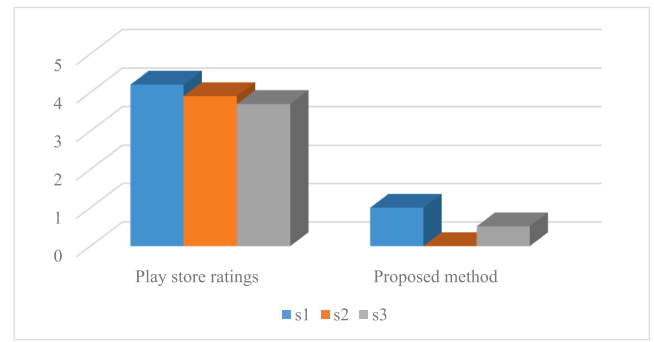


Fig. 3. Comparative analysis between the proposed method and the ratings estimated by the Google play store.

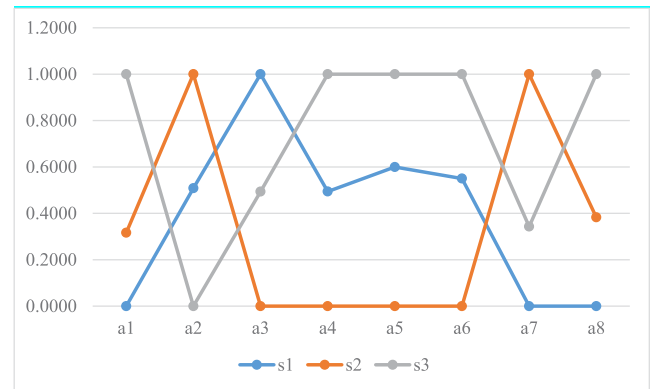


Fig. 4. Sensitivity analysis of the proposed method.

with 5 being the highest. Fig. 2 provides the comparative results of our proposed method and the ratings of the Google Play store.

From Fig. 3, the Google Play store ratings produce the ranking $s_1 \succ s_2 \succ s_3$. Our proposed method obtains the same best alternative s_1 from the Google play store. However, the positions of the alternatives s_2 and s_3 interchanged. Unlike the ratings, our method utilizes textual reviews provided by consumers. Text reviews contain more information than ratings (Darko et al., 2022; Darko & Liang, 2022). For instance, the consumer can express different sentiments in one text review instead of using a numerical value to rate the service. Extant studies (López Fernández & Serrano Bedia, 2004; Núñez-Serrano et al., 2014; R. Oliveira et al., 2013) have raised issues concerning the worth of ratings as a good estimator of performance. Therefore, using textual reviews in our proposed method delivers sufficient information to measure the effectiveness of the m-payment services.

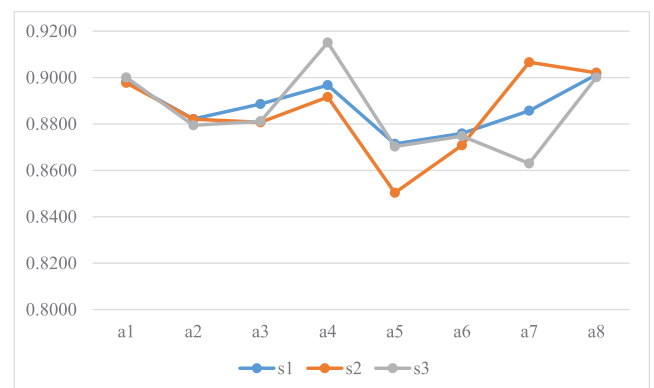


Fig. 5. Sensitivity analysis of the PLWA method.

Table 9
Wilcoxon signed-rank test p -values of rankings obtained by PLWA, PL-TOPSIS, PL-EDAS and the proposed method.

Methods	p -values
PLWA and PL-TOPSIS	0.109
PLWA and PL-EDAS	0.109
PLWA and our approach	0.285
PL-TOPSIS and PL-EDAS	0.109
PL-TOPSIS and our approach	0.109
PL-EDAS and our approach	1.000

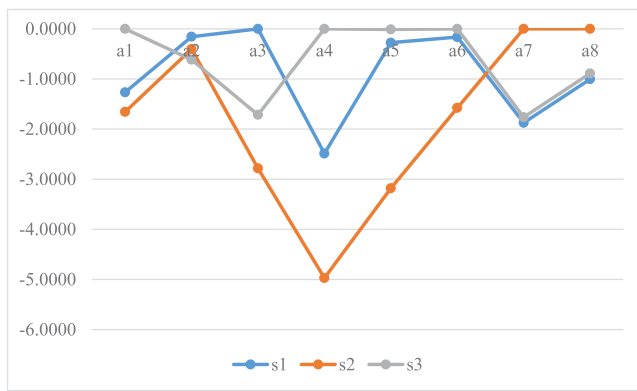


Fig. 6. Sensitivity analysis of the PL-TOPSIS method.

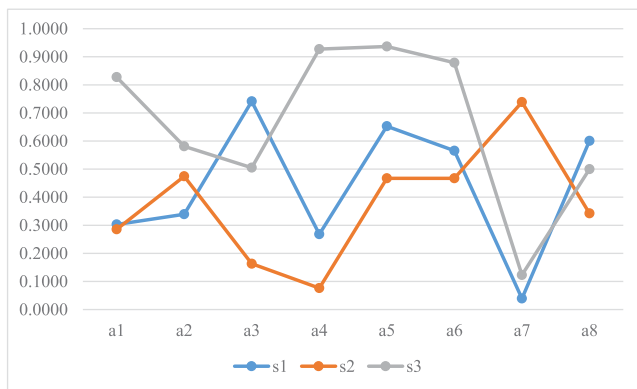


Fig. 7. Sensitivity analysis of the PL-EDAS method

During the decision analysis of the PL-MADM methods, the weights of the attributes play a vital role in ranking the alternatives. Hence, we perform a sentiment analysis by varying each attribute’s weight and observing the ranking results. Following Asante et al. (2022) we create eight scenarios. In each case, one attribute is assigned a higher weight of 0.5 while the remaining attributes share equal weights. The results of the weight variations are shown in Figs. 4–7.

From, Fig. 4 – 7, we observe that the weights of the attributes have a remarkable effect on the ranking results of the PL-MADM methods. This implies that using an objective weighting method, such as the proposed PL-ITARA method, is inevitable in determining the fair weights of the attributes. For our proposed method (Fig. 4), we detect that, except for the attribute a_3 , the ranking positions of the alternatives changed drastically with variations in the remaining seven attributes. The finding shows the criticality of the attributes; hence m-payment service providers should improve these attributes consistently to ensure good service performance. Also, the sensitivity analysis of the PL-MADM methods reveals that the PL-MADM methods show stability in the ranking results; however, our proposed method and the PL-EDAS produce better stability by ranking one alternative the best in five scenarios.

4.3. Implications for theory

In this paper, we present two theoretical implications of our study. First, our study offers a theoretical contribution by using text mining to identify new factors for evaluating m-payment usage. Second, we present a methodological contribution by developing an uncertain decision-making approach to evaluate and select appropriate m-payment services for business transactions.

As one of the disruptive technologies evolving globally, m-payment adoption research has increased recently. Many scholars employed

existing adoption theories and models for examining consumer behavior regarding m-payment adoption. This study extends the literature on adoption and service science by leveraging customer usage experiences via OCRs to identify m-payment usage attributes. We deepen the understanding of m-payment usage in an emerging economy like Ghana. This study is novel concerning evaluating and adopting m-payment using OCRs to our best knowledge. Our study highlights that apart from the traditional adoption models, attributes such as interface complexity, system update, verification, customer support, system functionality, service features, account registration, and security enhance m-payment experiences. These attributes significantly impact the usage behavior of consumers. Since these constructs have been identified, future research can attempt to validate the relationships between these constructs and m-payment adoption using multivariate regression analysis.

This study employs the mixed research methodology by integrating text mining analytics with uncertain MADM. This novel decision support methodology aids in identifying the salient attributes of m-payment usage and the practical evaluation and selection of m-payment services. Text mining analytics involves applying content analysis, such as sentiment analysis and topic modeling, to OCRs collected from online platforms such as the Google play store (Kar, 2021). Since we utilize OCRs instead of the traditional survey forms for data collection, this approach provides a novelty when examining m-payment usage, which is missing in the extant literature. Moreover, the existing adoption models fail to consider the uncertainties and vagueness of human evaluation responses. Hence, this study makes another significant contribution by utilizing probabilistic linguistic term sets to model the uncertainty and ambiguity of consumers’ usage experiences. The past literature on m-payment adoption only focuses on identifying the relationship between the adoption factors and consumer behavior. Therefore, this study moves further to develop a decision-making approach that can evaluate m-payment services and adopt the best service(s) afterwards. Such an approach will likely provide better tools for consumers to make better choices in the selection of m-payment services.

4.4. Implications for practice

Our study underlines the importance of attributes like interface complexity, system update, verification, customer support, system functionality, service features, account registration, and security as crucial to adopting m-payment services. The result shows that system functionality is the most important attribute influencing the usage of m-payment services. As a result, service providers should ensure that the usability and reliability of payment platforms are enhanced to drive the usage process. Also, security is a major concern for the usage of m-payment services. Service providers should build a platform where customers’ private information is secured. Service providers may frequently communicate with consumers to assure them that their information is secured and will not be given out without their explicit permission within or outside the firm for any unintended usage. Such communiqué on how the firm is respecting and withholding the confidentiality of the user can aid a lot in promoting usage. Account registration is another factor that influences m-payment usage. Service providers should create a payment platform that will be easy and convenient for consumers to register and use the services. When consumers find it difficult to register on such platforms, they are discouraged from using m-payment. Again, payment platforms should be updated frequently to fix technology bugs and consumers’ concerns. Interface complexity is the least essential attribute among the eight key attributes. For consumers to select and use m-payment services, the interface of the payment platform should not be complicated. The platform should be easy to navigate and conduct business.

Moreover, the proposed positive and negative ideal-based PL-ELECTRE I method provides means by which prospective consumers can evaluate the various m-payment services on the market and adopt the appropriate one. Prospective consumers will always rely on the usage

experiences shared by others to aid in their usage decisions. However, the OCRs shared by the existing consumers are voluminous; hence prospective adopters of m-payment services may find it challenging to read through before making decisions. Therefore, our proposed methodology offers an easy and robust approach to assist prospective consumers of m-payment services. In addition, service providers relying on our proposed model will understand how their m-payment services are performing on the market. Knowing the performance of m-payment services will enable providers to strategize and improve their services.

5. Conclusion

This paper proposes an uncertain multi-attribute evaluation model to evaluate m-payment services. To this end, the paper combines a text mining approach and an uncertain MADM technique to identify m-payment service usage attributes and utilize these attributes to evaluate and select m-payment service(s). The proposed decision model comprises the following phases: The first phase involves crawling OCRs of the m-payment services from the related websites utilizing a python crawler. The LDA topic modeling approach is employed in the second phase to extract the key usage attributes from the preprocessed text reviews. An unsupervised machine learning technique performs sentiment analysis on the text reviews concerning each attribute. Third, we convert the sentiment scores of the attributes regarding each m-payment service into PLEs and construct a probabilistic linguistic decision matrix. Fourth, a novel method, PL-ITARA, is designed to determine the importance weights of the usage attributes. In the last phase, we propose the positive and negative positive and negative ideal-based PL-ELECTRE I methodology to evaluate and rank m-payment services. The core innovations of this paper are outlined as follows: (1) This paper develops a novel evaluation approach, the positive and negative ideal-based PL-ELECTRE I method, which can objectively convert huge OCRs into PLTSs to avoid the problem of ambiguity and uncertainty in evaluating m-payment services. (2) The key usage attributes discussed in the OCRs are extracted based on the LDA topic modeling approach. This enables service providers to comprehensively understand the attributes influencing consumer usage behavior. (3) The study offers an approach through which OCRs can be modeled into PLTSs to avoid the fussiness and vagueness of OCRs. (4) Also, this paper objectively ascertains the weight of the usage attributes, which provides additional information to service providers and prospective consumers on the importance of these attributes. (5) Based on the positive and negative ideal solutions, this paper defines new outranking relations for PLEs. (6) To provide a complete ranking of m-payment services, this paper combines the strength of two methods, namely ELECTRE I, and the positive and negative ideal solutions.

It should be emphasized that the uncertain evaluation model developed in this paper applies to the selection of m-payment services but has the flexibility to be applied in other fields with similar processes, such as online ticketing, online shopping, etc. However, some limitations of this paper can be exposed. Firstly, this paper considers only OCRs from the same website. But there may be situations where a potential consumer may want to rely on OCRs from different websites for making a purchase decision. Hence, future studies may consider integrating OCRs from multiple websites. Secondly, this paper considers only text reviews as the data source. The heterogeneous online information (online reviews and ratings) can be utilized with MADM methods in future works. Furthermore, the language scale function can be improved to introduce the unbalanced effect of positive and negative evaluations.

CRedit authorship contribution statement

Adjei Peter Darko: Data curation, Investigation, Methodology, Writing – original draft. **Decui Liang:** Conceptualization, Supervision, Writing – review & editing. **Zeshui Xu:** Supervision, Writing – review &

editing. **Kobina Agbodah:** Data curation, Investigation. **Sandra Obiora:** Data curation, Investigation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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References

- Abirami, A. M., & Askarunisa, A. (2017). Sentiment analysis model to emphasize the impact of online reviews in Healthcare industry. *Online Information Review*, 41(4), 471–486.
- Agrebi, M., Abed, M., & Omri, M. (2017). ELECTRE I based relevance decision-makers feedback to the location selection of distribution centers. *Hindawi*, 10.
- Al-Saedi, K., Al-Emran, M., Ramayah, T., & Abusham, E. (2020). Developing a general extended UTAUT model for M-payment adoption. *Technology in Society*, 62. <https://doi.org/10.1016/j.techsoc.2020.101293>
- Asante, D., Ampah, J. D., Afrane, S., Adjei-Darko, P., Asante, B., Fosu, E., ... Amoh, P. O. (2022). Prioritizing strategies to eliminate barriers to renewable energy adoption and development in Ghana: A CRITIC-fuzzy TOPSIS approach. *Renewable Energy*, 195, 47–65. <https://doi.org/10.1016/j.renene.2022.06.040>
- Awajan, I., Mohamad, M., & Al-Quran, A. (2021). Sentiment analysis technique and neutrosophic set theory for mining and ranking big data from online reviews. *IEEE Access*, 9. <https://doi.org/10.1109/ACCESS.2021.3067844>
- Bai, C., Zhang, R., Qian, L., & Wu, Y. (2017). Comparisons of probabilistic linguistic term sets for multi-criteria decision making. *Knowledge-Based Systems*, 119, 284–291. <https://doi.org/10.1016/j.knsys.2016.12.020>
- Becker, L., & Jaakkola, E. (2020). Customer experience: Fundamental premises and implications for research. *Journal of the Academy of Marketing Science*, 48(4). <https://doi.org/10.1007/s11747-019-00718-x>
- Bojjagani, S., Sastry, V. N., Chen, C. M., Kumari, S., & Khan, M. K. (2021). Systematic survey of mobile payments, protocols, and security infrastructure. *Journal of Ambient Intelligence and Humanized Computing*. <https://doi.org/10.1007/s12652-021-03316-4>
- Çalı, S., & Balaman, Ş. Y. (2019). Improved decisions for marketing, supply and purchasing: Mining big data through an integration of sentiment analysis and intuitionistic fuzzy multi criteria assessment. *Computers and Industrial Engineering*, 129(December 2018), 315–332. <https://doi.org/10.1016/j.cie.2019.01.051>
- Cao, D., Meadows, M., Wong, D., & Xia, S. (2021). Understanding consumers' social media engagement behaviour: An examination of the moderation effect of social media context. *Journal of Business Research*, 122. <https://doi.org/10.1016/j.jbusres.2020.06.025>
- Cao, Q., & Niu, X. (2019). Integrating context-awareness and UTAUT to explain Alipay user adoption. *International Journal of Industrial Ergonomics*, 69. <https://doi.org/10.1016/j.ergon.2018.09.004>
- Cao, T. (2021). The study of factors on the small and medium enterprises' adoption of mobile payment: Implications for the COVID-19 era. *Frontiers in Public Health*, 9. <https://doi.org/10.3389/fpubh.2021.646592>
- Chaiyasoonthorn, W., & Suksangiam, W. (2019). The diffusion and adoption of electronic payment systems in Bangkok. *International Journal of E-Business Research*, 15(2). <https://doi.org/10.4018/IJEBR.2019040106>
- Chaurasia, S. S., Verma, S., & Singh, V. (2019). Exploring the intention to use M-payment in India: Role of extrinsic motivation, intrinsic motivation and perceived demonetization regulation. *Transforming Government: People, Process and Policy*, 13(3–4). <https://doi.org/10.1108/TG-09-2018-0060>
- Chen, K., Kou, G., Shang, J., & Chen, Y. (2015). Visualizing market structure through online product reviews: Integrate topic modeling, TOPSIS, and multi-dimensional scaling approaches. *Electronic Commerce Research and Applications*, 14(1), 58–74. <https://doi.org/10.1016/j.elerap.2014.11.004>
- Chiclana, F., Tapia García, J. M., del Moral, M. J., & Herrera-Viedma, E. (2013). A statistical comparative study of different similarity measures of consensus in group decision making. *Information Sciences*, 221. <https://doi.org/10.1016/j.ins.2012.09.014>
- Choi, H., Park, J., Kim, J., & Jung, Y. (2020). Consumer preferences of attributes of mobile payment services in South Korea. *Telematics and Informatics*, 51. <https://doi.org/10.1016/j.tele.2020.101397>

- Dahlberg, T., Guo, J., & Ondrus, J. (2015). A critical review of mobile payment research. *Electronic Commerce Research and Applications*, 14(5). <https://doi.org/10.1016/j.elerap.2015.07.006>
- Dahlberg, T., Mallat, N., Ondrus, J., & Zmijewska, A. (2008). Past, present and future of mobile payments research: A literature review. *Electronic Commerce Research and Applications*, 7, 165–181.
- Darko, A. P., & Liang, D. (2020). Some q-rung orthopair fuzzy Hamacher aggregation operators and their application to multiple attribute group decision making with modified EDAS method. *Engineering Applications of Artificial Intelligence*, 87. <https://doi.org/10.1016/j.engappai.2019.103259>
- Darko, A. P., & Liang, D. (2022). Modeling customer satisfaction through online reviews: A FlowSort group decision model under probabilistic linguistic settings. *Expert Systems With Applications*, 195(February), Article 116649. <https://doi.org/10.1016/j.eswa.2022.116649>
- Darko, A. P., Liang, D., Zhang, Y., & Kobina, A. (2022). Service quality in football tourism: An evaluation model based on online reviews and data envelopment analysis with linguistic distribution assessments. *Annals of Operations Research*. <https://doi.org/10.1007/s10479-022-04992-x>
- Fattoruso, G., Marcarelli, G., Grazia, M., Massimo, O., & Olivieri, M. G. (2019). Using ELECTRE to analyse the behaviour of economic agents. *Soft Computing*, 2. <https://doi.org/10.1007/s00500-019-04397-2>
- Flavian, C., Guinaliu, M., & Lu, Y. (2020). Mobile payments adoption – introducing mindfulness to better understand consumer behavior. *International Journal of Bank Marketing*, 38(7). <https://doi.org/10.1108/IJBM-01-2020-0039>
- Global Mobile Payment Market Expected to Reach \$ 4,574 Billion by 2023 – Allied Market Research. (n.d.). Retrieved December 10, 2021, from <https://www.prnswire.com/news-releases/global-mobile-payment-market-expected-to-reach-4574-billion-by-2023-allied-market-research-674829713.html>
- Hatefi, M. A. (2019). Indifference threshold-based attribute ratio analysis: A method for assigning the weights to the attributes in multiple attribute decision making. *Applied Soft Computing Journal*, 74, 643–651. <https://doi.org/10.1016/j.asoc.2018.10.050>
- Iman, N. (2018). Is mobile payment still relevant in the fintech era? *Electronic Commerce Research and Applications*, 30. <https://doi.org/10.1016/j.elerap.2018.05.009>
- Jocceviski, M., Ghezzi, A., & Arvidsson, N. (2020). Exploring the growth challenge of mobile payment platforms: A business model perspective. *Electronic Commerce Research and Applications*, 40. <https://doi.org/10.1016/j.elerap.2019.100908>
- Johnson, V. L., Kiser, A., Washington, R., & Torres, R. (2018). Limitations to the rapid adoption of M-payment services: Understanding the impact of privacy risk on M-Payment services. *Computers in Human Behavior*, 79, 111–122. <https://doi.org/10.1016/j.chb.2017.10.035>
- Jones, D. (2020). *Following COVID-19: How the virus is affecting the mobile payments industry*. News Features: Blockchain Technology.
- Jung, Y., & Suh, Y. (2019). Mining the voice of employees: A text mining approach to identifying and analyzing job satisfaction factors from online employee reviews. *Decision Support Systems*, 123, Article 113074. <https://doi.org/10.1016/j.dss.2019.113074>
- Kang, J. (2018). Mobile payment in Fintech environment: Trends, security challenges, and services. *Human-Centric Computing and Information Sciences*, 8(1). <https://doi.org/10.1186/s13673-018-0155-4>
- Kar, A. K. (2021). What affects usage satisfaction in mobile payments? Modelling user generated content to develop the “Digital Service Usage Satisfaction Model”. *Information Systems Frontiers*, 23(5), 1341–1361. <https://doi.org/10.1007/s10796-020-10045-0>
- Karimi, S., & Liu, Y. L. (2020). The differential impact of “mood” on consumers’ decisions, a case of mobile payment adoption. *Computers in Human Behavior*, 102. <https://doi.org/10.1016/j.chb.2019.08.017>
- Kaur, P., Dhir, A., Singh, N., Sahu, G., & Almotairi, M. (2020). An innovation resistance theory perspective on mobile payment solutions. *Journal of Retailing and Consumer Services*, 55. <https://doi.org/10.1016/j.jretconser.2020.102059>
- Khalilzadeh, J., Ozturk, A. B., & Bilgihan, A. (2017). Security-related factors in extended UTAUT model for NFC based mobile payment in the restaurant industry. *Computers in Human Behavior*, 70. <https://doi.org/10.1016/j.chb.2017.01.001>
- Khan, A., Abosuliman, S. S., Abdullah, S., & Ayaz, M. (2021). A decision support model for hotel recommendation based on the online consumer reviews using logarithmic spherical hesitant fuzzy information. *Entropy*, 23(4). <https://doi.org/10.3390/e23040432>
- Kumar, V., Nim, N., & Agarwal, A. (2021). Platform-based mobile payments adoption in emerging and developed countries: Role of country-level heterogeneity and network effects. *Journal of International Business Studies*, 52(8). <https://doi.org/10.1057/s41267-020-00346-6>
- Kwon, O., & Choi, R. (2022). Factors affecting the continuance intention of mobile payment services: A product-service systems perspective. *International Journal of Mobile Communications*, 1(1). <https://doi.org/10.1504/ijmc.2022.10037364>
- Liang, D., Dai, Z., & Wang, M. (2021). Assessing customer satisfaction of O2O takeaway based on online reviews by integrating fuzzy comprehensive evaluation with AHP and probabilistic linguistic term sets. *Applied Soft Computing*, 98. <https://doi.org/10.1016/j.asoc.2020.106847>
- Liébana-Cabanillas, F., Francisco Muñoz oz-Leiva, B., Sánchez-Fernández, J., Muñoz-Leiva franml, F., & Sánchez-Fernández sanchezf, ugres J. (2018). A global approach to the analysis of user behavior in mobile payment systems in the new electronic environment. *Service Business*, 12, 25–64. <https://doi.org/10.1007/s11628-017-0336-7>
- Liu, P., & Teng, F. (2019). Probabilistic linguistic TODIM method for selecting products through online product reviews. *Information Sciences*, 485, 441–455. <https://doi.org/10.1016/j.ins.2019.02.022>
- López Fernández, M. C., & Serrano Bedia, A. M. (2004). Is the hotel classification system a good indicator of hotel quality? An application in Spain. *Tourism Management*, 25(6). <https://doi.org/10.1016/j.tourman.2004.06.007>
- Lv, Z., Lou, R., Feng, H., Chen, D., & Lv, H. (2022). Novel machine learning for big data analytics in intelligent support information management systems. *ACM Transactions on Management Information Systems*, 13(1). <https://doi.org/10.1145/3469890>
- Mao, X. B., Wu, M., Dong, J. Y., Wan, S. P., & Jin, Z. (2019). A new method for probabilistic linguistic multi-attribute group decision making: Application to the selection of financial technologies. *Applied Soft Computing Journal*, 77, 155–175. <https://doi.org/10.1016/j.asoc.2019.01.009>
- Núñez-Serrano, J. A., Turrión, J., & Velázquez, F. J. (2014). Are stars a good indicator of hotel quality? Assymmetric information and regulatory heterogeneity in Spain. *Tourism Management*, 42. <https://doi.org/10.1016/j.tourman.2013.10.004>
- Olan, F., Suklan, J., Arakpogun, E. O., & Robson, A. (2021). Advancing consumer behavior: The role of artificial intelligence technologies and knowledge sharing. *IEEE Transactions on Engineering Management*. <https://doi.org/10.1109/TEM.2021.3083536>
- Oliveira, R., Pedro, M. I., & Marques, R. C. (2013). Efficiency and its determinants in Portuguese hotels in the Algarve. *Tourism Management*, 36. <https://doi.org/10.1016/j.tourman.2012.06.009>
- Oliveira, T., Thomas, M., Baptista, G., & Campos, F. (2016). Mobile payment: Understanding the determinants of customer adoption and intention to recommend the technology. *Computers in Human Behavior*, 61(2016), 404–414. <https://doi.org/10.1016/j.chb.2016.03.030>
- Ozturk, A. B., Bilgihan, A., Salehi-Esfahani, S., & Hua, N. (2017). Understanding the mobile payment technology acceptance based on valence theory: A case of restaurant transactions. *International Journal of Contemporary Hospitality Management*, 29(8). <https://doi.org/10.1108/IJCHM-04-2016-0192>
- Pang, Q., Wang, H., & Xu, Z. (2016). Probabilistic linguistic term sets in multi-attribute group decision making. *Information Sciences*, 369, 128–143. <https://doi.org/10.1016/j.ins.2016.06.021>
- Ren, P., Xu, Z., & Hao, Z. (2017). Hesitant fuzzy thermodynamic method for emergency decision making based on prospect theory. *IEEE Transactions on Cybernetics*, 47(9). <https://doi.org/10.1109/TCYB.2016.2638498>
- Roy, B. (1968). Classement et choix en presence de points de vue multiples (la methode ELECTRE). *Revue Informatique et Recherche Operationnelle*, 2(8).
- Shaw, N., Eschenbrenner, B., & Brand, B. M. (2022). Towards a mobile app diffusion of innovations model: A multinational study of mobile wallet adoption. *Journal of Retailing and Consumer Services*, 64. <https://doi.org/10.1016/j.jretconser.2021.102768>
- Singh, D. K., & Kaushik, P. (2019). Intrusion response prioritization based on fuzzy ELECTRE multiple criteria decision making technique. *Journal of Information Security and Applications*, 48, Article 102359. <https://doi.org/10.1016/j.jisa.2019.102359>
- Singh, N., & Sinha, N. (2020). How perceived trust mediates merchant’s intention to use a mobile wallet technology. *Journal of Retailing and Consumer Services*, 52. <https://doi.org/10.1016/j.jretconser.2019.101894>
- Slade, E., Williams, M., Dwivedi, Y., & Piercy, N. (2015). Exploring customer adoption of proximity mobile payments. *Journal of Strategic Marketing*, 23, 3209–3223.
- Teng, S., & Khong, K. W. (2021). Examining actual consumer usage of E-wallet: A case study of big data analytics. *Computers in Human Behavior*, 121. <https://doi.org/10.1016/j.chb.2021.106778>
- Tuffour, P., Opoku-Mensah, E., Asiedu-Ayeh, L. O., & Darko, D. (2021). Assessing governments response to exogenous shocks: Considering the COVID-19 pandemic in the Ghanaian context. *Journal of Public Affairs*. <https://doi.org/10.1002/pa.2755>
- Wang, J., & Lai, J.-Y. (2020). Exploring innovation diffusion of two-sided mobile payment platforms: A system dynamics approach. *Technological Forecasting and Social Change*, 157. <https://doi.org/10.1016/j.techfore.2020.120088>
- Webb, H., Liu, S., & Yan, M. R. (2019). Evaluation of M-payment technology and sectoral system innovation—A comparative study of UK and Indian models. *Electronics (Switzerland)*, 8(11). <https://doi.org/10.3390/electronics8111282>
- Wei, G., Wei, C., & Guo, Y. (2021). EDAS method for probabilistic linguistic multiple attribute group decision making and their application to green supplier selection. *Soft Computing*, 25(14), 9045–9053. <https://doi.org/10.1007/s00500-021-05842-x>
- Wixom, B. H., & Todd, P. A. (2005). A theoretical integration of user satisfaction and technology acceptance. *Information Systems Research*, 16(1). <https://doi.org/10.1287/isre.1050.0042>
- Yalcin, A. S., Kilic, H. S., & Delen, D. (2022). The use of multi-criteria decision-making methods in business analytics: A comprehensive literature review. *Technological Forecasting and Social Change*, 174. <https://doi.org/10.1016/j.techfore.2021.121193>
- Yu, S. M., Du, Z. J., Lin, X. D., Luo, H. Y., & Wang, J. Q. (2020). A stochastic dominance-based approach for hotel selection under probabilistic linguistic environment. *Mathematics*, 8(9). <https://doi.org/10.3390/math8091525>
- Zadeh, L. A. (1965). Fuzzy sets. *Information and Control*, 8(3), 338–353. [https://doi.org/10.1016/S0019-9958\(65\)90241-X](https://doi.org/10.1016/S0019-9958(65)90241-X)
- Zhang, D., Li, Y., & Wu, C. (2019). An extended TODIM method to rank products with online reviews under intuitionistic fuzzy environment. *Journal of the Operational Research Society*, 1–13. <https://doi.org/10.1080/01605682.2018.1545519>
- Zhao, M., Li, L., & Xu, Z. (2021). Study on hotel selection method based on integrating online ratings and reviews from multi-websites. *Information Sciences*, 572. <https://doi.org/10.1016/j.ins.2021.05.042>