Expert Systems With Applications 208 (2022) 118143

Contents lists available at ScienceDirect

Expert Systems With Applications

journal homepage: www.elsevier.com/locate/eswa

Knowledge graph of mobile payment platforms based on deep learning: Risk analysis and policy implications

Huosong Xia [a,b,c], Yuan Wang [a], Jeffrey Gauthier [d], Justin Zuopeng Zhang [e]

[a] School of Management, Wuhan Textile University, Wuhan 430073, China
[b] Research Center of Enterprise Decision Support, Key Research Institute of Humanities and Social Sciences in Universities of Hubei Province, China
[c] Research Institute of Management and Economics, Wuhan Textile University, Wuhan, 430073, China
[d] School of Business and Economics, State University of New York at Plattsburgh, Plattsburgh, NY 12901, USA
[e] Department of Management, Coggin College of Business, University of North Florida, Jacksonville, FL 32224, USA

ARTICLE INFO

Keywords:
Fintech
Mobile payment
Deep learning
Knowledge graph

ABSTRACT

The Fintech mobile payment platform is expanding rapidly; this expansion, in turn, creates numerous risks. There is an urgent need to better understand these risks and to spur more secure payment behavior. This research aims to develop knowledge graphs of the mobile payment platform based on deep learning for risk analysis and policy inferences. We identify entities from collected policy documents, extract the relationships among the entities, and draw a risk knowledge graph on mobile payments. The use of unsupervised semi-automatic knowledge acquisition, we argue, can reduce the risk of mobile payment caused by a lack of knowledge. A significant benefit of this method is that risk knowledge can be acquired without supervision. Unlike other models, the absence of manual labeling allows for the relation extraction of triples to be unsupervised, while the previous triplet extraction was supervised. Compared with other unsupervised models, the precision of our model is improved, and the recall is the same as that of previous unsupervised shutdown extraction. Unsupervised relationship extraction can extract text relationships quickly and on a large scale, saving human resources for labeling. This method offers a potential solution to a fundamental problem; the content and quantity of policy documents exceed organizations' and individuals' ability to understand them. Our approach suggests the viability of developing a national policy risk knowledge graph to help mobile payment platforms understand national policies and reduce platforms' operational risks while allowing users to quickly learn the risks of mobile payments and minimize the impact of those risks.

1. Introduction

Fintech is an emerging industry in which companies utilize innovative technology to provide financial services more efficiently (Chen, Wu, & Yang, 2019; Dranev, Frolova, & Ochirova, 2019; Liu, Li, & Wang, 2020; Ruan, Liu, & Tsai, 2021; Sheng, 2021). The development of Fintech and mobile banking has brought new opportunities for mobile payments but also presents unique challenges (Malaquias et al., 2021; Wamba et al., 2021). Security (Oliveira et al., 2016; Shao et al., 2019; Wang et al., 2020), trust (Zhou, 2013; Lonkani et al., 2020), and risk (Cocosila & Trabelsi, 2016) were identified as the most influential factors impacting mobile payment adoption. Risk has become an urgent problem for mobile payment; in the context of widespread and increasingly cybercrimes, mobile payment transactions bring significant financial risks (Pal et al., 2021b). While the mobile payment industry has matured, concerns about privacy and security risks remain (Albashrawi & Motiwalla, 2019). Although mobile payment is already an important method in the payment industry, it nonetheless holds risks that inhibit consumers' willingness to continue using it (Omigie et al., 2020; Sun et al., 2021). Security remains critical to promoting mobile payment services (Lim et al., 2019). A foundation of secure mobile payments may help to encourage government policies to enhance the use of mobile payments, promoting financial inclusion for all (Pal et al., 2021a). Notwithstanding security concerns, mobile payments have become an essential method in the payment industry (Du, 2018; Gomber et al., 2018; Iman, 2018).

As mobile payments continue to expand, risks of financial and data loss during transactions persist (Pal et al., 2021b). Policy documents help policymakers and planners make well-informed decisions (Nikolopoulos et al., 2021; Shih et al., 2021), enhancing an understanding

E-mail addresses: bxxhs@sina.com (H. Xia), jgaut003@plattsburgh.edu (J. Gauthier), justin.zhang@unf.edu (J.Z. Zhang).

https://doi.org/10.1016/j.eswa.2022.118143
Received 20 November 2021; Received in revised form 20 May 2022; Accepted 10 July 2022
Available online 16 July 2022

that, if lacking, could lead to decisions with significant negative consequences. The government has more comprehensive risk control than individual organizations and can implement effective policies to mitigate risks (Brandao-Marques et al., 2020). Therefore, extracting meaningful content from a large amount of text information in such policies has become imperative (Ullah et al.,2020). The analysis of policy documents can be used to better understand the content and mitigate risks (Sommer et al., 2017). The financial risk reduction of mobile payment enhances individuals' property security. Prior research has generally approached the avoidance of financial risks from a technical point of view, with a focus on ensuring the safety and reliability of software, but rarely from the perspective of users to reduce their financial risks; by contrast, our research aims to yield insights that reduce risks by enhancing users' risk knowledge.

A policy document offers two notable characteristics: it is goal-oriented and focuses on relevant segments of society (Yu et al., 2020; Yu et al., 2020). Policy documents can help policymakers and planners make informed decisions consistent with the direction the country is heading (Nikolopoulos et al., 2021). In the context of emergencies, governments formulate and implement policies to guide organizations or individuals (Demir & Danisman, 2021). Importantly, national policies play a central role in mitigating risks (Liu, 2021). Therefore, government documents are an appropriate source for individuals and organizations to study knowledge analysis of mobile payment risks. Mobile payment policy documents may be analyzed to ascertain the relationship between policies and the development of the mobile payment industry. Governments can gain valuable policy feedback to help improve their policies and, in the context of this paper's focus, better support the development of the mobile payment industry.

Developing a knowledge graph on strategic documents for the risk knowledge acquisition models offers significant promise for practitioners, helping them to understand and retrieve the relevant entity and related information. Deep learning (DL) has revolutionized many machine learning tasks, from image classification and video processing to speech recognition and natural language understanding (Wu et al., 2020). The development of DL technology has provided significant assistance for extracting the knowledge graph, and multiple variables are driving and contributing to this change (Kumar et al., 2021). As DL advances, data can be processed in almost raw form (Stevenson et al., 2021). When working with unstructured data, functions are handcrafted from data by experts or by indirect statistical transformations. Researchers have attempted to employ DL techniques to carry out research and exploration of the knowledge graph. However, improvements in computing performance have enabled the development of large neural networks with countless layers of neurons (Gunnarsson et al., 2021). This paper analyzes the published national policy documents, where DL has a vital role in handling a large amount of data.

As a new form of knowledge representation, knowledge graphs have attracted extensive attention in natural language processing (NLP) (Chen et al.,2020). It offers an improved ability to organize, manage, and understand the vast amount of data on the Internet, helping to reduce the cost of knowledge acquisition (Shi et al., 2021). Knowledge graphs can structurally describe the concepts, units, and relations of the objective world and express online information closer to the human cognitive world (Wang et al., 2021). In short, a knowledge graph has developed into a promising tool, using numerous entities and relations integrated into a graph (Li et al., 2021). The current knowledge graph on fusion can be broken down into three categories: path-based methods (Wang, Li, & Zeng., 2021), hybrid methods of embedding and path (Bai et al., 2021), and embedding-based methods (Guo et al., 2021). Knowledge graph has been widely applied for intelligent question answering (Do et al., 2021), decision-making assistance (Wang et al., 2020), disease prediction (Pham et al., 2022), plagiarism detection (Franco-Salvador et al., 2016), cyber threat intelligence (Sarhan & Spruit, 2021), and risk aversion (Yang and Liao, 2021). A knowledge graph is primarily constructed to extract textual information, the most important of which is relation extraction. There are three different methods of relation extraction: rule-based (Poonam et al., 2021; Sykes et al., 2021), supervised (Yu et al., 2020; Yu et al., 2020; Liu et al., 2020), and remote supervision relation extraction (Gu et al., 2019; Zhao et al., 2021), each of which has achieved good development. The knowledge graph has, in summary, been well-developed and provides support for our research and analysis of policy documents.

This paper will explore relation extraction using a combination of rules-based and unsupervised methods. The most common Neo4j graphics database is employed to visualize the knowledge graph. The Neo4j database is an open-source graph-oriented NoSQL database (Ravat et al., 2020) that has received increasing attention in recent years. This paper uses triples extracted from the text by the Neo4j database to construct knowledge graphs. Knowledge maps allow us to quickly view documents and extract meaningful relationships to help organizations and individuals understand policy documents. Knowledge graphs can help quickly retrieve industry rules, which is helpful for the operation of mobile payment platforms.

Specifically, we address the following research questions in this study:

RQ1. *What is the relation between relevant policy documents and the risks of mobile payment?*
RQ2. *How do mobile payment policies affect mobile payment risk knowledge identification through the knowledge graphs?*
RQ3. *How does the design of knowledge graph mining from mobile payment policies help identify the regularity of mobile payment risk knowledge?*

To answer these questions, we constructed a mobile payment knowledge graph based on DL to acquire risk knowledge and established a mobile payment knowledge graph model for policy documents. The model aims to provide helpful information for governments, businesses, and users.

The remainder of the paper is structured as follows. Section 2 reviews previous literature and constructs the knowledge graphs and experimental mobile payment model based on DL. Section 3 addresses the research process, including data acquisition and model verification experiments. Section 4 summarizes the outcomes of the experiment. Section 5 highlights the contributions, limitations, and future research directions of this paper.

2. Literature review and proposed model

2.1. Literature review

Mobile payment refers to the process of payment for products or services at any time and anywhere using mobile devices (Chang et al., 2021). It refers to not only the mobile payment methods but also the devices (e.g., wearable devices) to enable such methods (Lee et al., 2020). Mobile payment at the national level has two-sided network effects between consumers and retailers (Kumar et al., 2021), where the merchant trust plays a vital role in the adoption of mobile payment, considering the existence of mobile payment technology and security risks (Yeboah et al.,2020). As well, managers may have decision problems arising from understanding policy documents. Therefore, analyzing policy documents may be viewed as a way to control mobile payment risks.

Knowledge graphs can mine, organize, and manage knowledge effectively from large-scale data, improve information service quality, and provide more intelligent service for users (Chen et al., 2020). It is feasible to use knowledge graphs to analyze text to mine structured knowledge (Li et al., 2020; Li et al., 2020; Liu et al., 2020). Domain knowledge graphs (i.e., industry or vertical knowledge graphs) have more advantages than general domain knowledge graphs in this regard, but the domain knowledge graph is usually constructed manually,

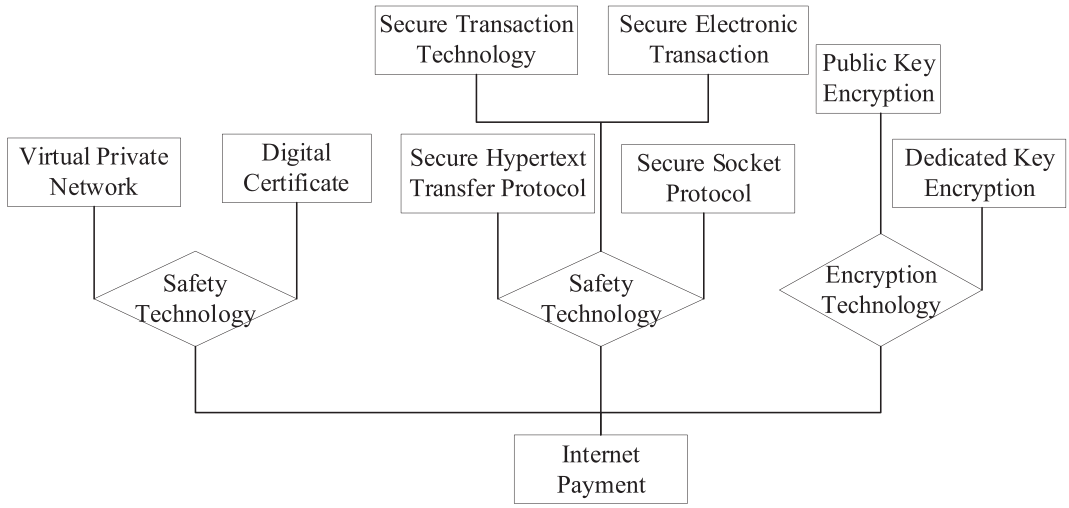


Fig. 1. Internet payment technology architecture diagram.

necessitating significant staffing and financial resources (Liu et al., 2020). Domain knowledge graphs are mainly applied to geographic information knowledge graphs, medical domain knowledge graphs, and e-commerce knowledge graphs, among other areas. The geographic information knowledge map is primarily represented in the form of entities and attributes, which are identified in the form of manual marking (Yang et al., 2018). The medical knowledge graph is constructed by using structured data to build triples describing medical concepts, relationships, and attributes (Byambasuren et al., 2019). The most apparent difference between the e-commerce knowledge graph and the previous two graphs is the use of a graph as a bridge to establish a connection between the two graphs (Xu et al., 2020). Combined with the above construction of the domain knowledge graph, we found that most domain knowledge graphs are based on structured and semi-structured data; there were some deficiencies in the construction of knowledge graphs using unstructured data.

NLP has become a topic of increased interest in management research because of its ability to automatically analyze and understand human language (Kang et al., 2020). NLP can be divided into three levels: vocabulary, syntax, and semantic and pragmatic processing (Chen & Luo, 2019). NLP technology can extract text entities and relationships (D'Souza & Auer, 2021). This makes it possible to construct the knowledge graph of mobile payment risk.

Against this backdrop, this paper aims to acquire knowledge of mobile payment risks from the perspective of knowledge graphs. We propose the knowledge acquisition model for attaining mobile payment risks based on the DL of knowledge graphs. Grounded by knowledge management theory combining technology and management, we obtain risk knowledge semi-automatically. We conduct experiments using data crawled from policy documents on the official website of the People's Bank of China to ascertain the effectiveness of the model.

2.2. Theoretical research perspective and model

2.2.1. Technical risks of mobile payment platforms

5G technology has been recently applied in mobile payment with Near Field Communication (NFC), providing two-way wireless proximity communication between mobile phones (Madureira, 2017).

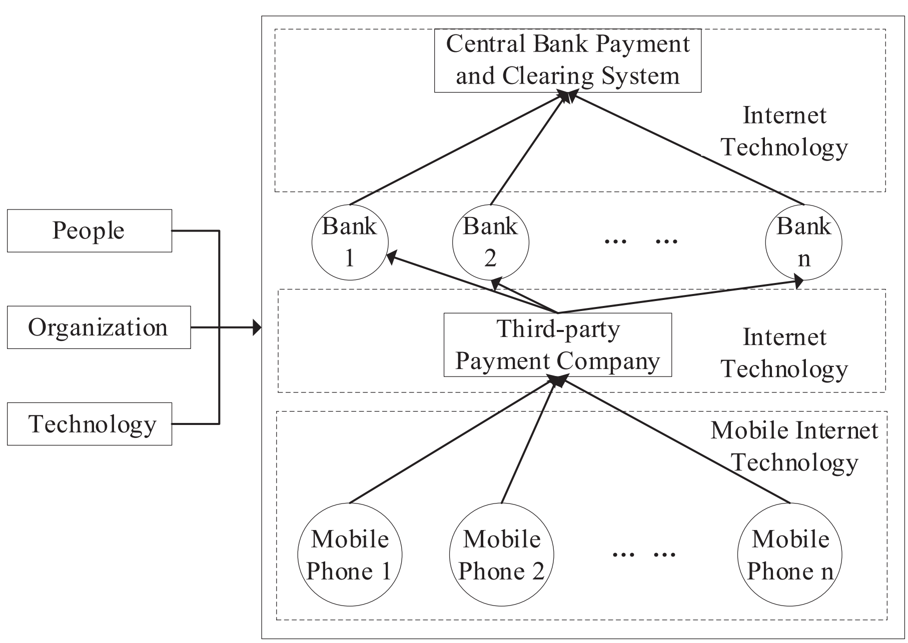


Fig. 2. Flow chart of mobile payment.

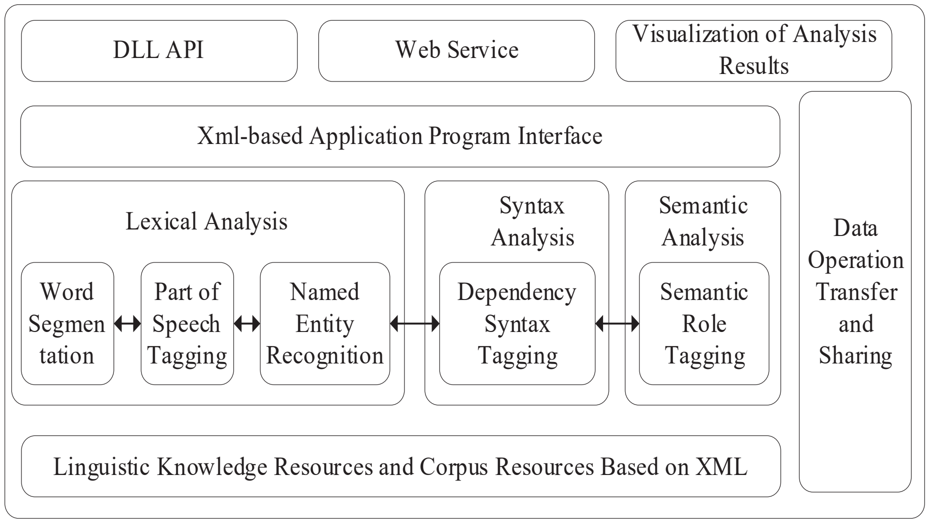


Fig. 3. LTP language technology platform architecture.

Mobile payment technology continues to spread globally, but its spread is uneven (Pal et al., 2021a). Smartphone-based mobile payment systems should be widely used in a variety of environments. The development of mobile payment is inseparable from the development of the Internet (Qasim & Abu-Shanab, 2016). The network technology required for Internet payment technology is presented in Fig. 1.

Depending on the amount of the payment, the mobile payment can be divided into micro-, small, and major payments. Notable examples of mobile payments include Android Pay, Samsung Pay, and Apple Pay (Loh et al., 2020). Different mobile payment involves different security mechanisms, encryption technology, authentication method, firewall, and other technologies that impact mobile payment security (Ahmed et al., 2021; Ahmed et al., 2021). Mobile devices allow customers to make close-range mobile payments with the convenience of NFC (Tew et al., 2021). Perceived risk is the most important factor influencing users' willingness to use NFC (Cocosila & Trabelsi, 2016). Although mobile payment is convenient in the process of use, the potential risks of mobile payment may force users to pay a considerable price (Choi et al., 2020).

As the range of payment methods continues to emerge in the market, the application of mobile payment is increasingly widespread. According to three aspects—people, organization, and technology, the mobile payment workflow is illustrated in Fig. 2.

Prior research on the risks of mobile payment platforms has mainly focused on how to reduce the risks of mobile payment platforms from a technical perspective and what risks may affect users' use of mobile payment platforms. This paper studies mobile payment risks from the standpoint of policy documents and establishes a knowledge acquisition model based on knowledge graphs. The research results help prevent the risks on mobile payment platforms for individuals and facilitate the corresponding process of operations and supervision for the government.

2.2.2. *Policy effect*

Policy documents issued by the government focus on national decision-making—policymakers working in uncharted territory must make difficult decisions (Nikolopoulos et al., 2021). Many scholars have analyzed the effect of policies in different countries. For instance, Mouna and Jarboui (2021) examine the impact of government policies on promoting financial inclusion in the Middle East and North Africa. Roberts et al. (2021) conclude that China's release of national-level policy documents reflects the intention to develop and deploy artificial intelligence (AI) in multiple fields. Ahmed et al. (2021), Ahmed et al. (2021) found that monetary policy impacts real estate output growth, labor employment, value-added change, and pricing trends.

However, there are limited studies on policy suggestions for the diffusion of mobile payment (Pal et al., 2021a); this topic is our paper's focus. Public policy impacts the gap between intent and actual adoption of mobile payments (Yeh, 2020). Understanding implications at the policy level can help determine the adoption of mobile payments (Gretzel et al., 2020; Law et al., 2018). However, prior research has been broad and not limited to the impact of mobile payments; the significant impact of current policies on mobile payments remains unclear (Law et al., 2019). Therefore, this study considers the policy dimension of mobile payment technology and foregrounds this topic as the focus of our research.

The governance of mobile payment platforms cannot be separated from the supervision and guidance of governments. The analysis of policy documents can help mobile payment platforms avoid risks. As well, the standard of policy formulation, implementation, and impact of policy on industrial development are issues that governments need to consider. Under the guidance of policy documents, users can reduce the risks arising from the use of mobile payment.

2.2.3. *Knowledge acquisition*

Knowledge Acquisition refers to the process of acquiring new knowledge and building upon it (Al-Emran & Teo, 2020). From the perspective of knowledge management, knowledge acquisition can discover valuable information from massive data and realize knowledge transformation and sharing. It can be stored in the domain's knowledge base to provide suggestions for resolving related issues (Xia et al., 2019).

Knowledge acquisition is closely related to machine learning (Castro et al., 2001). In the era of machine learning and DL, AI systems trained on biased data may lead to epistemological deficiencies in many cases. However, knowledge acquisition can present easily applicable user-centered and value-oriented dialogical guidelines (Gerdes, 2020). Knowledge acquisition is the acquisition of entities and concepts as a mapping dictionary (Li et al., 2020; Li et al., 2020; Liu et al., 2020), where the generalization of supervised annotation data is considered (Badgett & Huang, 2016). The diversity of information collection, including structured and unstructured data, helps to improve classification accuracy and new knowledge acquisition (Lei et al., 2020). Some scholars use topic models and association rules to acquire risk knowledge of mobile payment (Li et al., 2019). However, topic extraction will impact the subsequent association analysis to acquire knowledge. The process of knowledge acquisition can be divided into two key dimensions: knowledge graph completion and entity and relationship extraction (Abu-Salih et al., 2021). We take an unsupervised approach to

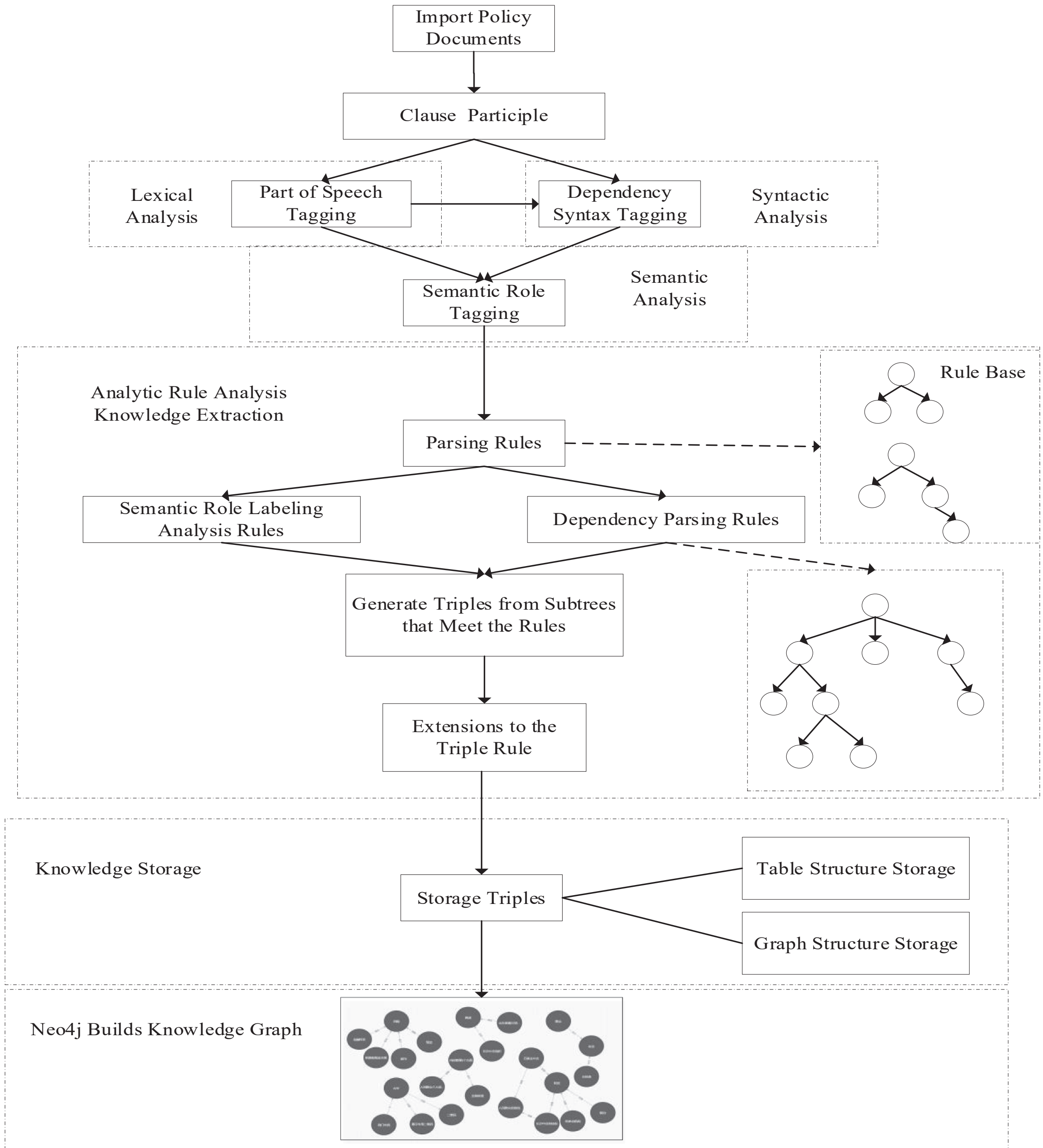


Fig. 4. Knowledge graph construction process.

acquire triplets, visualize knowledge maps, and finally accomplish knowledge acquisition.

2.2.4. *Model framework*

We propose to construct knowledge graphs on mobile payment based on DL using Python's PYLTP library (Zou et al., 2020). Its functions include word segmentation in Chinese, tagging parts of speech, recognizing named entities, tagging dependencies, and tagging semantic roles. The architecture of the LTP language technology platform is shown in Fig. 3. From an application perspective, LTP delivers the following components to users: 1) tools to generate statistical machine learning templates for individual NLP tasks; 2) the programming interface for model analysis for a single NLP task; 3) system runnable model file for Chinese processing; and 4) cloud-based programming interfaces for a single NLP task (Cao et al., 2020).

This paper analyses the impact of policy documents on mobile payment risks by building a knowledge graph of policy documents. First, the mobile payment policy documents were broken down into sentences and words. Second, tasks such as part of speech tagging, dependency syntax, and semantic role tagging were performed. Finally, information and event extractions were obtained by designing logical rules, where the Neo4j database was used to establish nodes and relations for visualization. The risk knowledge acquisition model is shown in Fig. 4.

3. Research method

Aiming at the requirement of knowledge acquisition in the mobile payment domain, a knowledge graph model is constructed based on DL technology.

The research in this paper includes the preprocessing of policy documents, the analysis of the part-of-speech tagging, the dependency syntax, and the semantic role tagging of text by PYLTP and the Neo4j

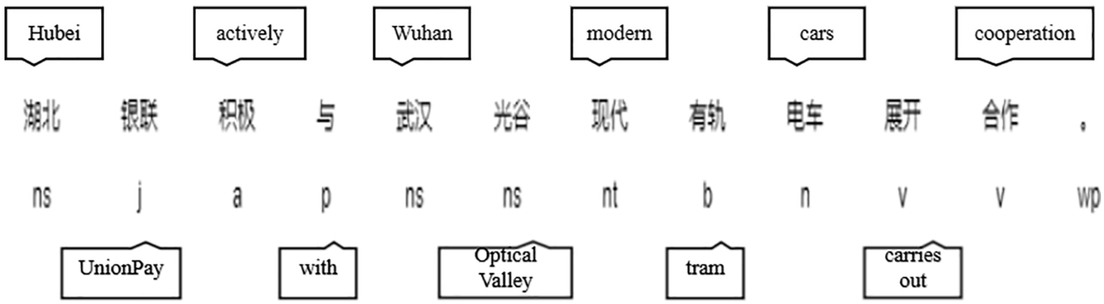


Fig. 5. Word segmentation results.

database. Then, we study the direct dependency relation between words by the semantic tagging of the role, as subject-verb-object, subject-copula-predictive, etc., to extract the triples. Finally, the Neo4j database was used to represent nodes and relationships to build a knowledge graph and analyze the impact of policy documents on mobile payment.

3.1. Data

On May 13, 2021, the official website of the People's Bank of China disclosed information, a total of 451 mobile financial services news, and financial IC card records about Fintech. This paper obtains relevant knowledge from the mobile payment policy documents obtained by a crawler. With the official arrival of the first year of Chinese mobile payment in 2014, an unprecedented revolution has taken place in the field of payment. Giants like Baidu, Alibaba, or Tencent (BAT) actively deploy mobile payment as it is a new, important mobile commerce application. Data before 2013 has been deleted, and data from 2014 to date has been maintained. Finally, post-2012 registrations were manually sorted to find news about mobile payment. Policy documents including "Fintech," "Mobile Payment," "Mobile Payment," "Mobile Finance," "Third Party Payment Facility," "Cloud Flash Payment App," "QR Code Payment," "In-person Payment," "WeChat," and "Alipay" were maintained. Policy documents containing "IC Financial Cards," "Banking Institutions," "Blockchain Technology," and policies unrelated to mobile payments were removed. "Electronic Payment," "Electronic Money," "Contactless Consumption," "Telecom Fraud," and "Network Security Education" may belong to the traditional mobile payment or IC card payment. It is necessary to analyze if these documents are biased to a certain type of document. A total of 356 documents were retained, including 2 documents in 2014, 3 documents in 2015, 5 documents in 2016, 10 documents in 2017, 66 documents in 2018, 143 documents in 2019, 116 documents in 2020, and 11 documents in 2021; the retention rate is 78.34 %. The text content is divided according to the time. The policy documents in different periods are analyzed to obtain different policy knowledge about China's mobile payment development. We divided 2014–2016 policy documents into a single category, 2017–2018 policy documents into a single category, and 2019–2021 policy documents into a single category.

3.2. Preprocessing

We started with the policy document and split the whole document; colons, semicolons, exclamation marks, etc., were used as the identifiers of segmentation to avoid affecting the subsequent dependency syntax analysis.

Part of speech tagging refers to the formulation of the part of speech of each word after a sentence is segmented. Each sentence is segmented and tagged using the PYLTP segmentation module. This paper takes the sentence "Hubei UnionPay actively carries out cooperation with modern tram cars in Wuhan Optical Valley" as an example to construct part of speech tagging. The results are shown in Fig. 5.

PYLTP uses 863 parts of speech tagging set and the model matches to

Table 1
PYLTP's part of speech table.

Label	Description	Example	Label	Description	Example
a	adjective	beautiful	ni	organization name	the United Nations
b	other noun-modifier	Large, Western style	nl	location noun	suburb
c	conjunction	although	ns	geographical name	Beijing
d	adverb	very	nt	temporal noun	Recently, the Ming Dynasty
n	general noun	apple	nz	other proper nouns	the Nobel prize
v	verb	run, study	p	preposition	On, put
i	idiom	a hundred flowers bloom	q	quantity	a
nd	direction noun	left side	r	pronoun	We
nh	person name	Du Fu, Tom	U	auxiliary	of
m	number	First, the first	V	verb	run, study
wp	punctuation	,。!	J	abbreviation	Public Security Organs

get the part of speech of each word after word segmentation. The meanings of each part of speech are shown in Table 1. For example, the 'a' tag means that the word is an adjective, the 'v' tag means that the word is a verb, etc. All words after the segmentation have a word label, which can be matched in the table below.

3.3. Dependency syntactic and semantic role annotation based on PYLTP

The parser inputs each stage from the process to the split, as shown in Figs. 5, 6, and 7, and all stages in the process are one after the other.

3.3.1. Dependency parsing

Dependency parsing is also called syntactic analysis, one of the key technologies in NLP. The analysis of dependency was initially proposed by the French linguist L. Tesniere, with the intent to parse the sentence as a dependency analysis tree and indicate the dependency relations between each word. Based on dependency parsing, a syntax tree is established for each sentence in the text (Chen et al., 2019). In other words, it highlights the syntactic relation of co-occurrence between words, which is related to meaning.

Dependency parsing reveals its syntactic structure by analyzing dependencies among components within a language unit. Correlation parsing identifies the grammatical components of a sentence, such as "subject-predicate-object" and "fixed adverbial complement." Correlation parsing can analyze the relations between the components. The sentence "Hubei UnionPay actively carries out cooperation with modern

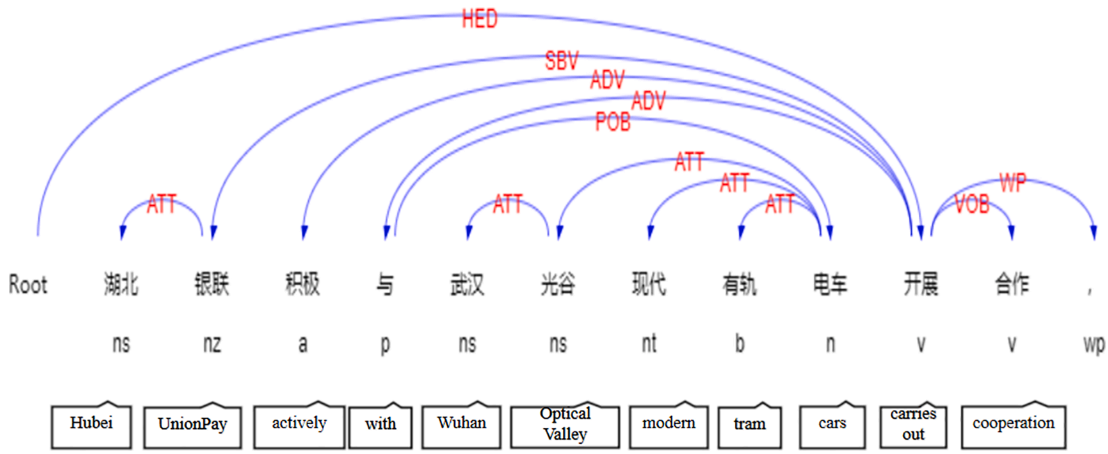


Fig. 6. Dependency parsing result.

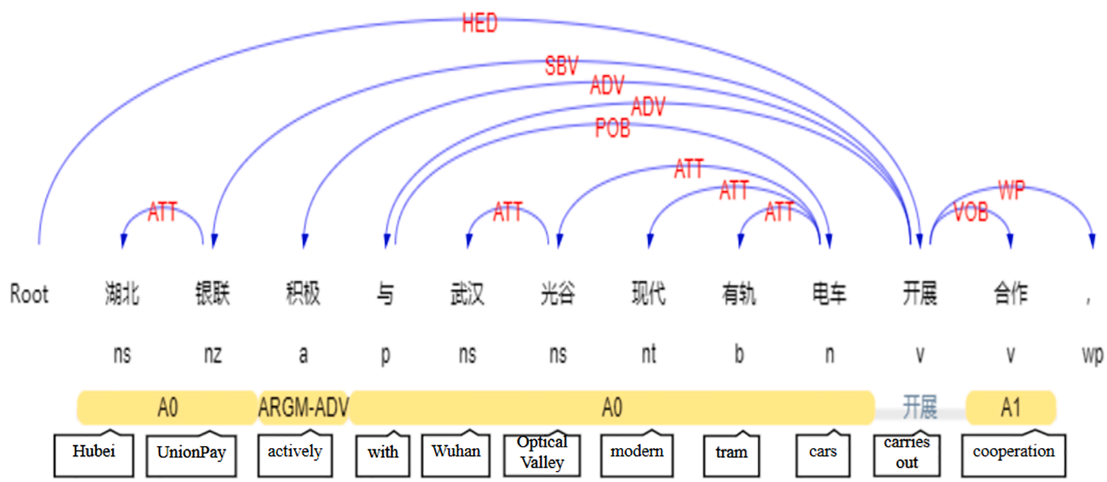


Fig. 7. Semantic role labeling results.

Table 2
TPYLTP pendency syntax table.

Relation type	Label	Example
Subject-verb relation	SBV	I sent her a bunch of flowers (I < –sent)
Verb-object relation	VOB	I sent her a bunch of flowers (sent –> flowers)
Indirect-object relation	IOB	I sent her a bunch of flowers (sent –> her)
Attribute relation	ATT	A red apple (red < –apple)
Adverbial relation	ADV	very beautiful (very < –beautiful)
Preposition-object relation	POB	Within the trade zone (within)
Independent structure	IS	Two single sentences are structurally independent of each other
Core relation	HED	Refers to the core of the sentence

tram cars in Wuhan Optical Valley” is analyzed as follows. PYLTP dependency parsing model (parser. model) was used to parse the part-of-speech tagged sentences. The interrelation between words is illustrated in Fig. 6.

Table 2 shows that there are adverbial relations, attribute relations, head relations, preposition-object, subject-verb relations, and verb-object relations between each word in this sentence. Combining Fig. 6 and Table 3, we can analyze the example sentences. The core relationship is the verb “carries out,” which is the core of the sentence, and the main action of the sentence is around the word. The adverbial structure is between “carries out” and “actively”; “actively” is used as the

Table 3
PYLTP semantic role labeling table.

Relation Type	Tag	Description	Example
ARG0 (A0)	Causers or experiencers	Agent, subject, trigger	[The Government ARG0] encourages individual to invest in the service industry.
ARG1 (A1)	Patient	Recipient	The government encourages [individual ARG1] to invest in the service industry.
ADV	Adverbial	Adverbial	We [immediately ADV] coming ushered in the new year.
BNF	Beneficiary	Beneficial owner	Obligation [for schoolchildren and teachers BNF] to do ultrasound examination.
CND	Condition	Condition	[If caught early CND], the patient can be alerted to changes in blood pressure
CRD	Coordinated arguments	Juxtaposition	They are also more active in pursuing peaceful relations with South Korea [and the US CRD]
LOC	Locative	Location	Please listen to the report from VOA special correspondent Connie [in Vancouver, Canada LOC].

Note: ARGM-XXX, for example, time, place, purpose, degree, scope, etc. ARGM-ADV is adverbial; ARGM-BNF is beneficiary; ARGM-CND is a condition, and ARGM-DIR is direction.

adverbial of "carries out." This is a modification of the verb "carries out" using the adverb "actively." In the attribute relation, "modern," "Optical Valley," and "tram" are the attributives of "cars," "UnionPay" is the attributive of "Hubei," and "Wuhan" is the attributive of "Optical Valley." In other words, the attribute relation is the use of modifiers to modify the description of the noun. The preposition-object relation is "with." It is usually added with a noun or a noun phrase. The subject-verb relation is between "UnionPay" and "carries out." This is a noun–verb structure that can form a complete sentence. The verb-object relation is between "carries out" and "cooperation." This relation consists of a verb plus a noun or pronoun, giving a receiver to a given action. The subject-verb-object of this sentence is "UnionPay carries out cooperation." We can find the real sentence relationships according to our own needs and prepare for the extraction of triples through dependency parsing.

3.3.2. *Semantic role labeling*

Semantic role labeling is a shallow semantic analysis technology to analyze sentence predicate-argument structures according to sentences. The theoretical basis is the syntax proposed by Fillmore (1968). Specifically, the role of semantic labeling is to concentrate on the predicate, studying the relationship between the predicate and sentence components. Semantic roles explain the relationships between different roles. After completing the dependency parsing in the previous step, the sentence "Hubei UnionPay actively carries out cooperation with modern tram cars in Wuhan Optical Valley" is marked with semantic roles labeling. The result is shown in Fig. 7.

Combining Table 3 with Fig. 7, we can observe that there are two A0, one A1, and one ADV in this sentence. A predicate is the core word of a sentence, usually a verb or an adjective. The agent, subject, and trigger A0 of this sentence are "Hubei UnionPay" and "modern tram cars in Wuhan Optical Valley." These two are in parallel relation. Both of these words denote the person who acts. The recipient A1 is "cooperation." This is the receiver of the action. The adverbial ArgM-ADV is "actively" as an adverbial of "carries out." This analysis of the main components of the sentence allows for triplet extraction to pave the way.

3.4. *Analyze relation extraction based on parsing rules*

3.4.1. *Information extraction triples*

The information extraction triples are mostly based on the triple extraction of the dependency syntax. First, for each word, the child node of the subordinate grammar of the word, the primary storage relation, and the position of the child word is generated. Then, for each word, the subordinate structure of the parent–child array of the word is generated, which mainly records the part of speech of the word, the part of speech of the parent node, and the relation between them. Subsequently, the cycle of each word finds and extracts the verb-object relation, the verb-object relation after the attribute relation, and the subject-predicate-verb-complement relation of the preposition and the object. The specific relationship is shown in Table 2. Finally, to extract words from the subject and object, it is necessary to find words with related subordinate structures and remove unnecessary words.

3.4.2. *Event extraction triples*

The semantic role of PYLTP is used for labeling phrases if the subject-predicate-object (SPO) structure is present in the statistics. If present, the SPO structure is extracted, which guarantees the quality and accuracy of the generated triplet (Papadopouloset al., 2020); if not, the SPO structure is extracted by substitution syntax. It is necessary to extract the fact triples centered on the predicate, including the subject-predicate-object relation. The attributive postposition and the verb-object relation contain the subject-predicate-verb-complement relation with the intermediate object relation. The main purpose is to find the predicate verb of each sentence and then mark the semantic role according to the verb to find that A0 and A1 constitute subject-predicate-object. The verb

Fig. 8. Word cloud.

Table 4
Top 10 words in 2020 documents.

Ranking	Keyword	Counts	Ranking	Keyword	Counts
1	finance	659	6	experimental unit	136
2	technology	506	7	work	135
3	application	264	8	innovate	119
4	payment	194	9	financing institution	107
5	develop	167	10	promote	104

is equal to that event. A0 is the agent, and A1 is the recipient, triples of the subject-predicate-object extraction events.

3.5. *Word cloud*

After preprocessing, we select the 2020 Policy document and use Python's collection and word cloud library to generate a word graph, as shown in Fig. 8. In the statistics of word cloud graphs, the frequency of words is distributed according to the size of the font. Stated differently, the larger the font, the more frequently the word appears. It can be seen from Fig. 8 that in the central topic with "finance" and "payment" as keywords, "application," "payment," "develop," and "experimental unit" are the more important central parts, which reflect the continuous development and innovation of mobile payment in China. It is worth noting that mobile payment was initially widely used by people to pay for public transport. There have been campaigns to encourage more users to pay with their phones, increasing mobile payment usage. At the same time, mobile payments are developing more rapidly. Secondly, with the widespread promotion of the "cloud flash payment APP," scanning QR codes for payment becomes more convenient, and security work and social engineering will be a focus of people's attention (Chang et al., 2021; Jansen van Rensburg, 2021). Finally, mobile payment carries risks when used, notwithstanding the potential benefits of use. It forces the national government to confront the issue of online fraud aggressively. We can find the development direction and risks of mobile payment in China in the policy documents, which organizations and individuals need to understand and avoid.

Table 4 links the above-mentioned top-of-mind concepts, which are linked in four broad categories: "Fintech," "mobile payment APP," "technological innovation," and "third-party payment platform." Below each major category are related categories; for example, under "Fintech," there are "finance" and "technology." The development of technology promotes the development of finance and provides new products and services for the traditional financial industry. Under "mobile payment APP," there is "application," "payment," etc. The security of

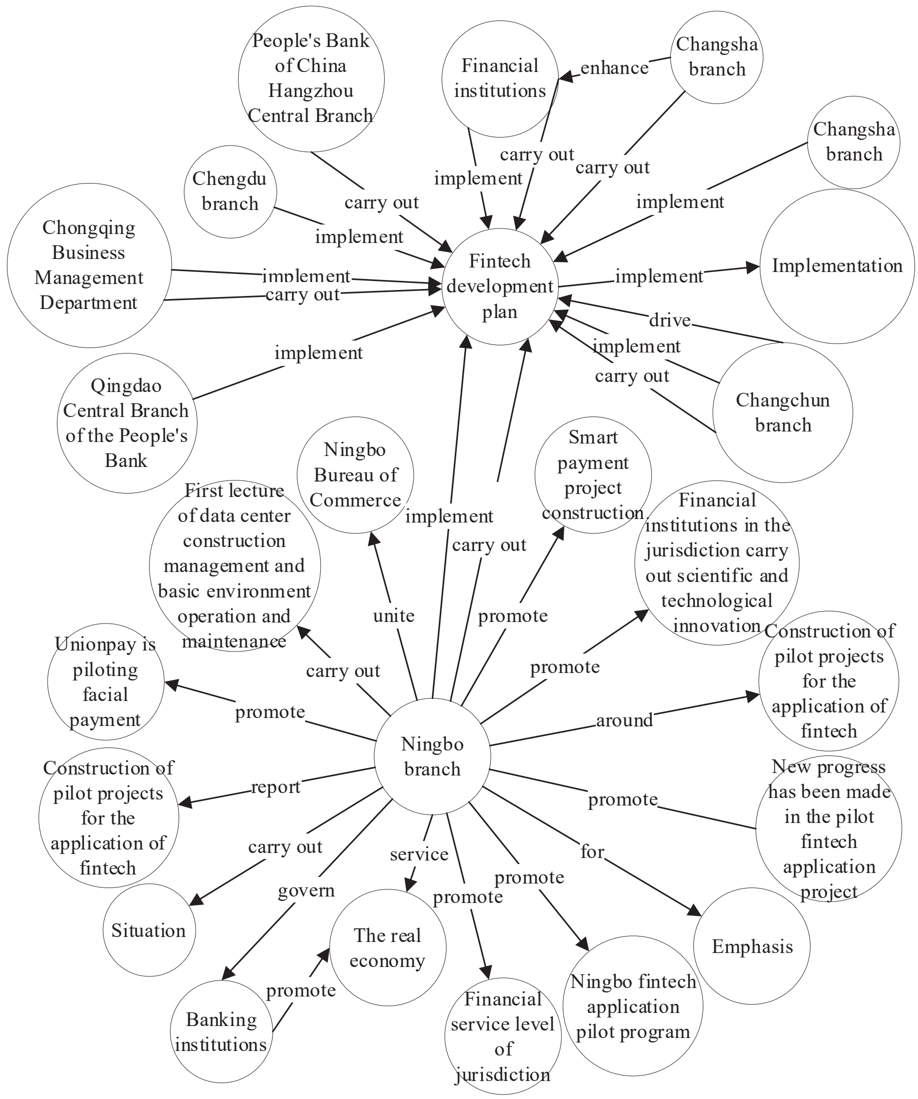


Fig. 9. Knowledge graph.

mobile payment application software ensures the security of users' property. Under "Technological innovation," there is "development," "innovation," "promotion," etc. The continuous innovation of science and technology makes the rapid development of mobile payment. Under "third-party payment platform," there are "financial institutions," etc. The development of third-party mobile payment platforms cannot be separated from the supervision of financial institutions. Finally, after all the categories and relations are established, the core category is defined as "under the innovation of financial technology and technology to promote the development of mobile payment APP of third-party payment platform" during the core login process. After further analysis of the original data under this theoretical framework, two grounded theories are developed: 1) China's Fintech industry achieves technological innovation, and 2) the third-party payment platform mobile payment APP is continuously developing.

4. Experimental results and analysis

Given the risks of mobile payments, it is imperative to gain knowledge from the vast array of cumbersome policy documents. Through knowledge acquisition, mobile payment-related knowledge can be mined to help mobile payment literacy and to help mobile payment users and managers mitigate risks. Risk can be deduced by using a knowledge graph.

4.1. Knowledge graph analysis

The knowledge graph is a new concept launched by Google in 2012. From a theoretical perspective, the knowledge graph is essentially the knowledge foundation of the meaning network. The knowledge graph can be understood as a multi-relation graph for simple understanding and practical application. The most important attribute of the knowledge graph is the entities and relations. Different entities are connected by extracting relations to form a knowledge graph. The knowledge graph can quickly find the information sought. Because the knowledge graph has a visualization function, it can help understand the information searched by users and summarize the content related to the search topic.

This paper provides a visual analysis of the 2020 policy documents and triples extraction based on the principle of combining rule-based and unsupervised relationship extraction. The main process includes preprocessing, part of speech tagging, dependency parsing, semantic role labeling, and relation extraction based on parsing rules. The model extracts a total of 1443 sets of triples and uses manual methods to remove non-conforming triples, leaving 1216 groups with a retention rate of 84.27 %. The knowledge graph is shown in Fig. 9. This is part of the triplet extracted from the policy document in 2020. It primarily describes the construction plan of mobile payment in Ningbo and the adoption of UnionPay to promote the development of mobile payment.

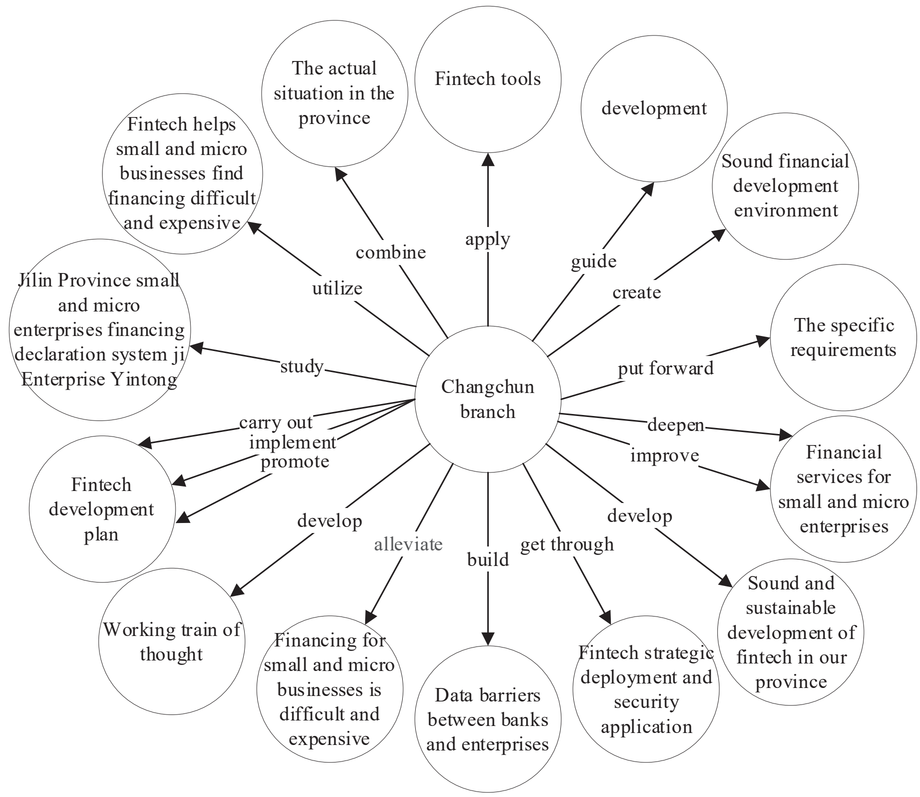


Fig. 10a. Knowledge graph-Changchun branch.

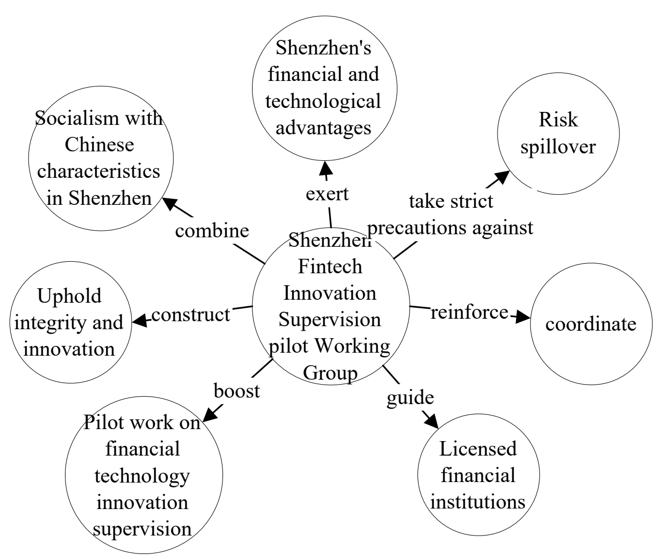


Fig. 10b. Knowledge graph: Shenzhen Fintech Innovation.

Table 5
The Risk Terms (Top 15).

Number	Word	Number	Word
1	Risk	9	Digital Certificate
2	Pain Difficult	10	Phishing
3	Telecommunication Fraud	11	Account Information
4	Mass Texting	12	Root
5	Hacker	13	Operating System
6	Theft	14	Prevention and Control
7	WIFI	15	Supervise
8	QR code		

Ningbo uses banking institutions to promote economic development, construct smart payment projects, and cooperate with Changsha, Chengdu, Changchun, and Qingdao to strictly implement Fintech development plans.

It is less difficult to understand policy documents by using the knowledge graph. Extracting the relationships between entities provides a quick snapshot of how attitudes towards mobile payments have evolved in China over the past year. A semi-automatic risk triad in mobile payment can be found by mining the relevant risk knowledge in the field of mobile payment. Fig. 10(a) shows the reform of the Changchun branch combined with the actual province of financial services of small and micro enterprises in using Fintech to alleviate the difficulty of financing for small and micro-enterprises. The Changchun branch developed the financing declaration system for small and micro enterprises in Jilin Province. This system gets through the data barriers between banks and enterprises, speeds up the strategic deployment and security application of Fintech, and creates a good financial development environment. This illustrates the country's support of mobile payment. At the same time, mobile payment has security, lack of funds, and other risks. Mobile payment may also be exposed to the risk of personal information leakage and users' personal property being threatened due to the broken fund chain. Fig. 10(b) demonstrates how Shenzhen Fintech Innovation regulatory pilot working group gives full weight to Shenzhen's financial and technological advantages in combination with Building integrity and innovation of Socialism with Chinese characteristics in Shenzhen. Using Shenzhen's Fintech advantages can guide licensed financial institutions, strictly prevent risk spillovers, and create an atmosphere of integrity and innovation. We discovered that there are risk overflows, and the company's risks affect the surrounding businesses and facilities, thus keeping a distance from the surrounding security protection. Therefore, mobile technology companies should develop technological innovation and control risk spillover factors. Users need to evaluate risks when using third-party payment platforms, mainly for technological innovation and risk spillover.

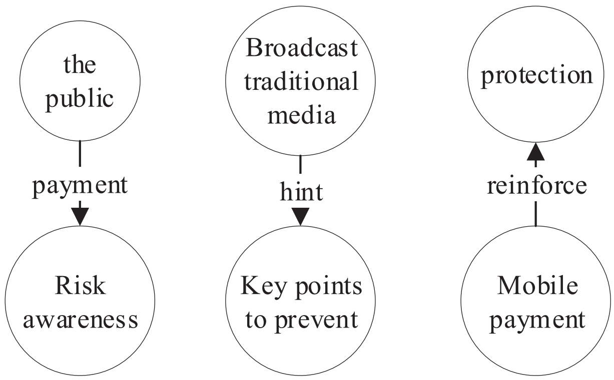


Fig. 11. 2014–2016 Risk knowledge graph.

4.2. Risk knowledge acquisition

Risk represents the harmfulness of uncertain losses and outcomes. The mobile payment risk vocabulary is constructed manually, as shown in Table 5. If the triplet extract contains the sentence in the vocabulary, it is considered as having a risk of mobile payment. These triples with risk awareness are built to obtain the mobile payment risk awareness graph as shown in Figs. 11, 12, 13. Keywords are extracted from the policy documents of a certain period to get the payment hot spots in that period intuitively. For example, from 2014, China's mobile payment was mainly based on bank cards, while in 2019 and 2020, due to the development of science and technology, China's mobile payment seems to be primarily based on cloud flash payment. A tally of these keywords showed that the word with the highest frequency was a fraud, suggesting the need to raise people's awareness of the risks. Therefore, mobile payment risk knowledge acquisition and research are timely and important topics.

The risk knowledge graph from 2014 to 2016 is shown in Fig. 11. The public is aware of mobile payment security, broadcasting traditional media to remind users to guard against risks and strengthen mobile payment protection. Through the risk knowledge graph, we can infer payment risks in mobile payment and inform users to avoid them during payment. For example, there are risks like bank card theft and user information leakage in mobile payment.

The risk knowledge graph from 2017 to 2018 is shown in Fig. 12. First, it can be seen that the usage rate of mobile payment keeps rising, the UnionPay QR code has become the primary way of mobile payment, and mobile payment scenarios have also increased. But for users, the main risk of mobile payment comes from the threat of QR code leakage. Therefore, we should protect our QR codes in the payment process and strictly prevent the risk of property and information leakage to ourselves.

The risk knowledge graph from 2019 to 2021 is shown in Fig. 13. First, through the risk knowledge graph, we can ascertain that various institutions and banks have taken measures to strengthen the prevention and control of mobile payment and protect people's property security. This indicates that the process of using mobile payments still carries risks. When using mobile payment platforms, users need to be more aware of prevention and protect their legitimate rights and interests from violation. According to the knowledge graph, to protect personal information and financial security, each agency conducted a comprehensive survey on five aspects of internal control management. It found several problems, such as bugs in many apps that allow hackers to monitor the phone's interface in real-time, take screenshots, and capture important account information during payments. Therefore, QR code protection is essential in the payment process. There are two significant security risks. First, the information storage capacity of two-dimensional code is dozens or even hundreds of times that of bar code. QR codes can be used as Trojan horses or phishing websites to leak information such as account passwords and steal property. Second, the QR code also has the characteristics of simplicity and low cost, making it easy to copy. In the face of these risks, the policy document also provides potential solutions, such as ensuring users' payment security, improving laws and regulations on mobile payments, accelerating pilot projects on fintech applications, and reducing risks caused by cash transactions. At the same time, different provinces have been reminded of the risks of mobile payment. Users should improve their risk awareness, pay attention to the confidentiality of personal information, refrain from sharing personal information with strangers, avoid insecure network connections, be mindful of the need to protect other important information, such as ID numbers, passwords, digital mobile phones, use dynamic passwords, and exercise caution with suspicious email, so as not to suffer from the risk of Trojan horse virus.

With the development of technology, the risks of mobile payment continue to increase. Mobile phones with NFC functions are expensive, so QR code payment is China's primary mobile payment method. The leak of the QR code leads to the insecurity of mobile payment, which has been the most significant security risk for the development of mobile payment in China. Therefore, the design and use of QR codes are crucial for the government, mobile payment platforms, and users. Payment platforms should improve the QR code technology so that users can protect their QR codes from being used by others in the process of payment.

4.3. Risk knowledge reasoning

In planar knowledge-based reasoning, methods include rule-based, neural network, distributed representation, and mixed reasoning.

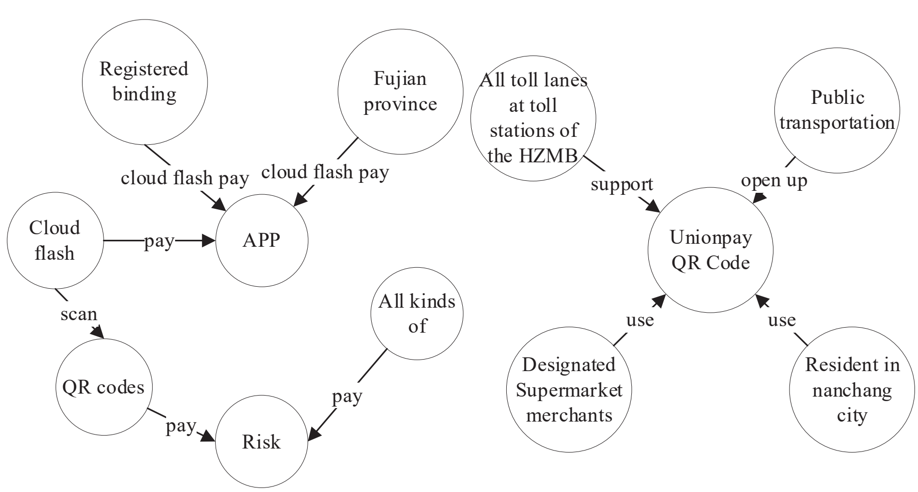


Fig. 12. 2017–2018 Risk knowledge graph.

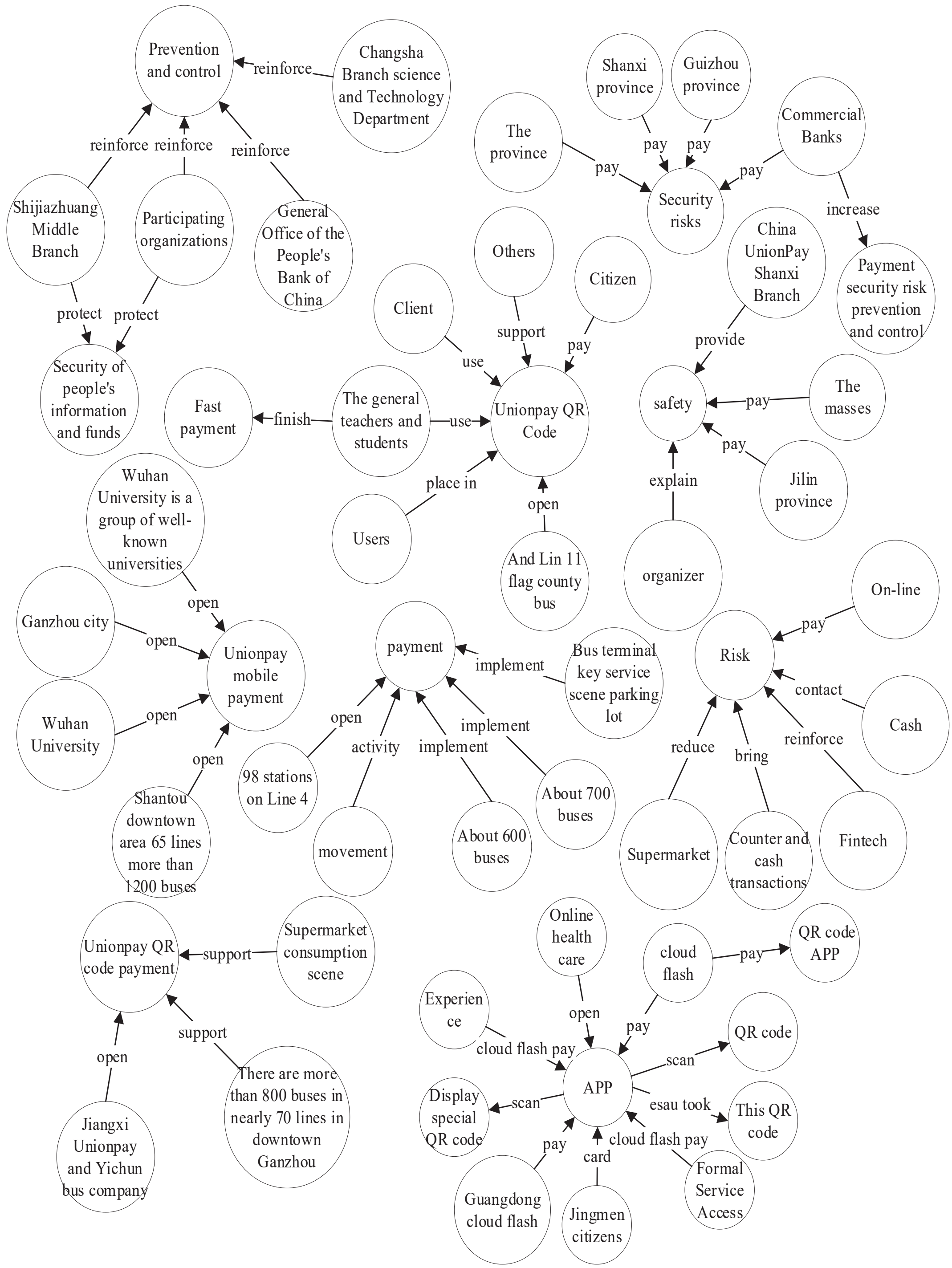


Fig. 13. 2019–2021 Risk knowledge graph.

Among them, rule-based reasoning plays a vital role in achieving knowledge (Yu et al., 2021). Rule-based reasoning refers to a formal description of experts' knowledge in areas related to forming systematic rules.

As shown in Fig. 14, we discover risk knowledge and perform knowledge reasoning. First, the rules of mobile payment risk knowledge graph are constructed for "The People's Bank of China Hangzhou Central Branch guides financial technology to strengthen risks," i.e., [ruleRisks: (?p: guidance?m) (?m: strengthen?g) -> (?p:prevent?g)]. As shown in Fig. 15:

Combining Figs. 14 and 15, we can conclude that there are risks in the "QR code," "APP application," "transaction process," "personal information leakage," and "network fraud," which has gained the attention of enterprises and consumers. We have also discovered the rule that when entities similar to the above nodes appear in the knowledge graph. There are mobile payment risks in this knowledge graph, which need to be avoided by enterprises and users.

4.4. Knowledge graph model Comparison

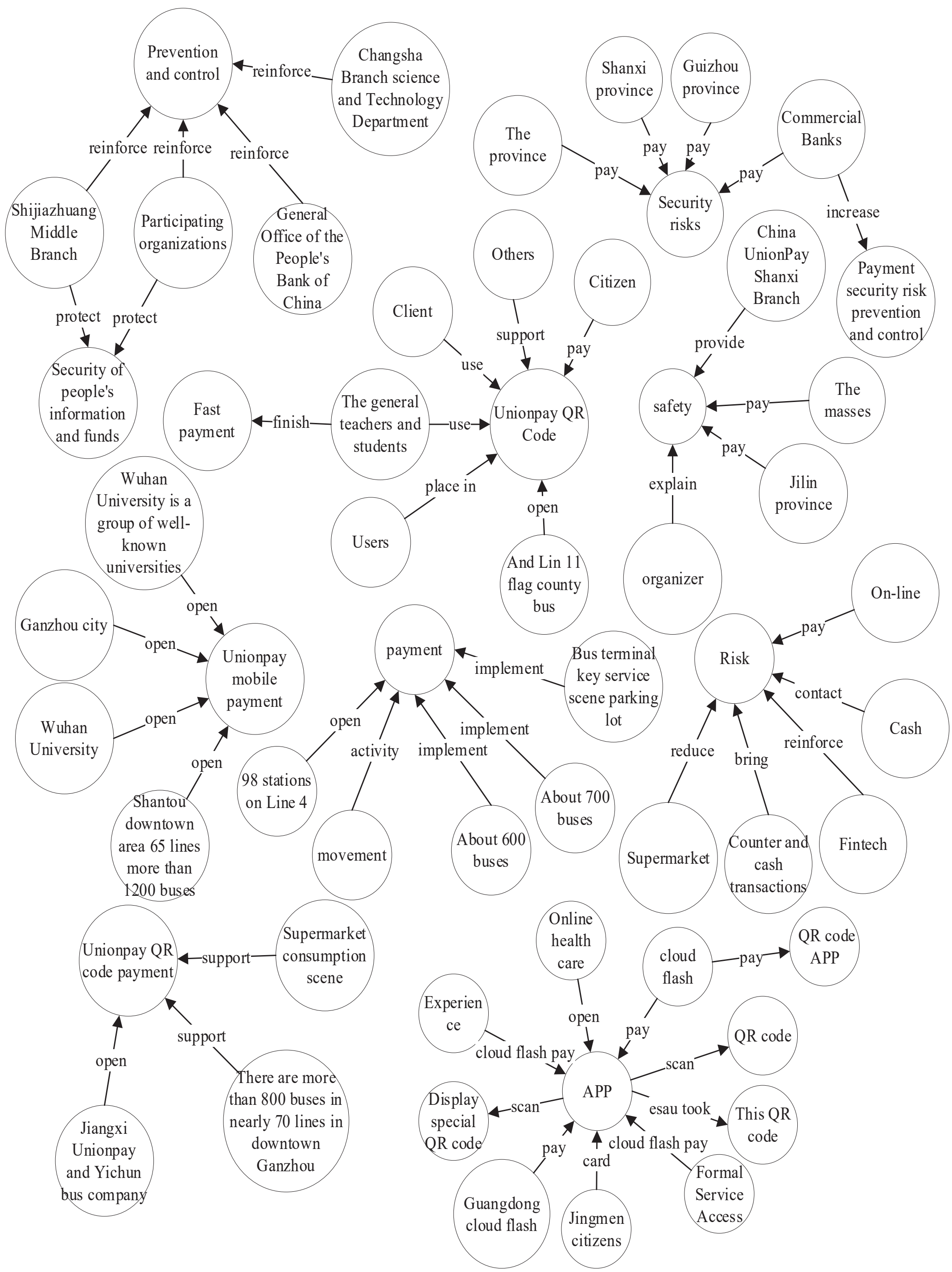
The key to constructing a knowledge graph is relation extraction. Here, we mainly compare the triplet relationship extraction model, from rule-based, supervised, and remote supervised to unsupervised relationship extraction. The results are shown in Table 6. We summarize the comparison of different relationship extraction models. Compared with previous supervised learning methods, the unsupervised method we propose is easier to use and saves manual marking resources. Compared with unsupervised relational extraction, our proposed model has good performance in precision and recall rate. According to the extraction rules, our model does not need a manual operation to extract triples and can apply to any field as unsupervised methods save a lot of manpower and resources. At the same time, the visualization of relation extraction of this model has been greatly improved.

The method used in this article belongs to the unsupervised method based on undefined entity-relationship types in advance. As there is no way to use artificial corpus collection and the relationship between the entity annotation, it cannot be directed by the program to draw the result for judging right or wrong (Qin & Liu, 2015), so this paper adopts the way of artificial judgment to determine whether candidates relation triples are classified correctly. Thus, precision (P) and recall (R) are used to evaluate the method's performance, as shown in Equations (1) and (2).

$$P = \frac{TP}{TP + FP} \times 100\%, \tag{1}$$

$$R = \frac{TP}{TP + FN} \times 100\%, \tag{2}$$

where TP is the number of correctly classified samples in the cluster, FP is the number of incorrectly classified samples in the cluster, TF is the correctly extracted number of relationships, and ($TP + FN$) is the actual total number of relationships.



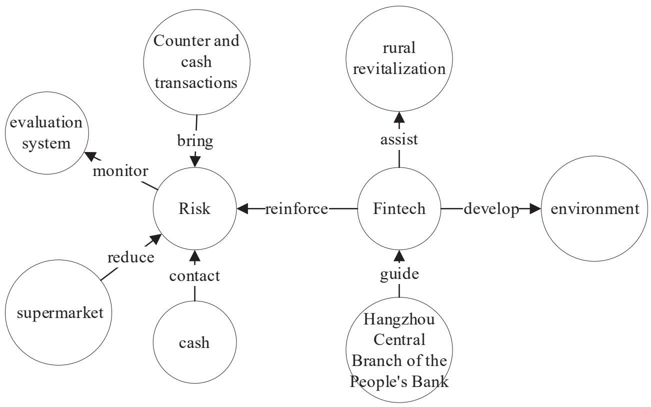


Fig. 14. Risk knowledge graph-Fintech.

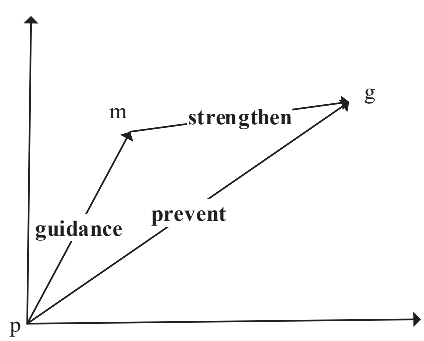


Fig. 15. The risk of rule.

.

Compared with the advanced unsupervised relation extraction algorithms, the precision of the proposed model is improved. However, in terms of recall rate, our model is even lower than Bert's relational extraction model and better than other advanced unsupervised relational extraction models, as shown in Table 7. At the same time, the precision and recall of supervised relationship extraction can reach more than 90 % (Liu et al., 2020), but there is still a particular gap between unsupervised relationship extraction. However, the unsupervised relationship extraction model saves a lot of human resources in manual marking. At the same time, the efficiency of relationship extraction has certain accuracy, which can apply to fast and large-scale text relationship extraction (Takase et al., 2015).

5. Discussions and conclusions

We construct a research framework for knowledge acquisition to address the risk problem in mobile payment. The release of relevant policy documents can remind users and platforms of the risks of using mobile payment and obtain the knowledge of reducing mobile payment. First, we broke the mobile payment policy document into different terms and built the mobile payment vocabulary. Then, we used Python code to do simple text mining of the policy document. The main process included preprocessing, part of speech tagging, dependency parsing, semantic role labeling, and relation extraction based on parsing rules. Second, relational extraction based on parsing rules can effectively learn text context information extraction triples, for which the Neo4j database is used for visualization. Combined with knowledge graph reasoning, risk knowledge can be acquired. Relational extraction reduces the number of manually created tags compared to other supervised extraction methods (Zhao et al., 2021; Papanikolaou et al., 2019). Compared with advanced unsupervised relation extraction algorithms, the precision of this model is improved by about 4 %. However, in terms of recall, our model is lower than Bert's relational extraction model by about 1 %, which is better than other advanced unsupervised relational extraction

Table 6
Comparison of relation extraction algorithms.

Type	Model	Article Title	Author/Time	Characteristic
Rule-based relational extraction	Stanford parser	Design of Relation Extraction Framework to Develop Knowledge Base.	Poonam et al., 2021	Concept generation, attribute extraction, and hierarchical relation extraction were analyzed at the sentence level by the dependency parsing tree.
	Bidirectional long - short-term memory (Bi-LSTM) network	Comparison of rule-based and neural network models for negation detection in radiology reports.	Sykes et al., 2021	Extract structured information from the original text of an electronic health record (EHR).
Supervised relation extraction	Convolution residual networks based on an improved cross-entropy loss function	A relation extraction method for domain knowledge graph construction.	Yu et al., 2020	The hierarchy is obtained in semi-structured data.
	An end-to-end multi-level semantic representation enhancement network	Multi-level semantic representation enhancement network for relation extraction.	Liu et al., 2020	Enhancing entities at the word, phrase, and context level to extract deeper semantic information.
Remotely supervised relation extraction	Remote supervision based on attention mechanism	Chemical-induced disease relation extraction via attention-based distant supervision.	Gu et al., 2019	Attention-based neural networks and stack self-coding networks are used to induce the learning model and extract the hierarchical relation, respectively.
	Syntax relies on tree and ontology constraints for remote supervision	Research on syntactic dependency tree and Ontology constraint in remote Supervising relation extraction.	Zhao et al., 2021	The position weight of each word in the sentence is obtained by the syntactic dependency tree, and domain ontology constraint is introduced to improve the accuracy of relation extraction.
Unsupervised relation extraction	A hierarchical graph-based clustering technique	A graph-based clustering approach for relation extraction from crime data.	Das et al., 2019	The weighted graph was formed according to the similarity score. The similarity threshold was set and the graph was divided according to the edge weight.
	BERT	Deep bidirectional transformers for relation extraction without supervision.	Papanikolaou et al., 2021	The data set is used to fine-tune a pre-trained BERT model to perform relational extraction.
	LDA and Topic *N*-Grams	Semantic relation extraction aware of *N*-gram features from unstructured biomedical text.	Wang et al., 2018	Rel-tng and Type-TNG are proposed based on the topic-*n*-grams (TNG) model, and the folded Gibbs sampling algorithm is used for inference.
	Unsupervised dependency syntactic and semantic role annotation using PYLTP (Our method).			According to extraction rules, extracting triples does not need manual work and applies to any field. The unsupervised approach saves a lot of manpower and resources.

Table 7
Comparison of unsupervised relation extraction algorithms.

Method	Article Title	Author/time	Precision	Recall
A hierarchical graph-based clustering technique	A graph-based clustering approach for relation extraction from crime data.	Das et al., 2019	72 %	82 %
BERT	Deep bidirectional transformers for relation extraction without supervision.	Papanikolaou et al., 2021	75.5 %	85.1 %
LDA and Topic *N*-Grams	Semantic relation extraction aware of *N*-gram features from unstructured biomedical text.	Wang et al., 2018	80.09 %	82.45 %
Dependency syntactic and semantic role annotation			84.27 %	83.36 %

models. At the same time, the precision and recall of supervised relation extraction can reach more than 90 % (Liu et al., 2020), and there is still a gap between unsupervised and supervised relation extraction. However, the unsupervised relation extraction model saves more human resources for manual annotation. At the same time, the efficiency of relation extraction has a certain accuracy, and it can be well applied in fast and large-scale text relation extraction (Takase et al., 2015). Finally, the model is used to construct the knowledge map of mobile payment policy semi-automatically, and the extracted relational triplet can help identify the mobile payment risk knowledge. Based on the relationship between entities, the risk knowledge between different entities is analyzed to discover mobile payment risk knowledge regularly.

5.1. Theoretical contribution

This paper proposes a research method based on a knowledge graph to obtain more fine-grained mobile payment risk knowledge from the knowledge management perspective. It fills the theoretical gap of mobile payment risk research and discovers the regularity of mobile payment risk, from a bank card to QR code risk transformation. Organizations and individuals can mitigate risks if they can understand the policy documents. The policy documents can promote the reduction of mobile payment risks. Moreover, this research has guiding significance for users' mobile payment, platform operation, and governments' mobile payment governance.

This paper constructs a knowledge acquisition model of mobile payment risk based on a knowledge graph. From a knowledge management perspective, PYLTP libraries were used to map dependencies on syntactic and semantic roles. Triples were extracted based on rules and unsupervised relationship extraction, and then the knowledge of mobile payment risk was visualized by the Neo4j database. The main contribution of this method is that risk knowledge can be acquired without supervision. Without manual labeling, the most significant difference between this and other models is that the relation extraction of triples is unsupervised, while the previous triplet extraction is mainly supervised. Compared with previous unsupervised relational extraction models, the proposed unsupervised relational extraction model achieves a certain degree of royalty in accuracy, while the recall is not improved much compared with previous algorithms. However, our model has a good performance in large-scale text extraction triplet forming knowledge map, which can save the waste of resources for article labeling. This method solves a fundamental problem concerning the contents and quantity of policy documents – specifically, size and complexity inhibit organizations' and individuals' ability to understand policy documents. Under the guidance of knowledge management theory combining technology and management, we propose a new method of acquiring and sharing risk knowledge related to mobile payment semi-automatically.

5.2. Practical contribution

First, using our proposed model to extract the primary relations from policy documents can help the general public quickly understand the rules and industry risks identified by the country. Regarding knowledge of risks on the Internet, the knowledge graph template can be used to extract explicit knowledge of risks rapidly. For governments, the knowledge graph can be built according to the rules and risk knowledge extracted from the policy documents, in combination with the policy effect, providing suggestions to the government and making policy changes. The government can improve policies to oversee the platform's operation and achieve the objective of platform governance. Governments have promoted awareness of the risks of QR codes for mobile payments and, by extension, the platform and user security more broadly. For platform management, the visual knowledge graph can help managers quickly obtain the rules of platform operation to promptly regulate their users' behavior on the platforms (Hung et al., 2021) and achieve the objective of platform governance. The platform requires governance through technical means to continuously optimize the QR code and enhance its security index. For mobile payment users, by using the knowledge graph, they can easily and quickly understand the risk knowledge in mobile payment. Thus, users can hope to avoid losses through this knowledge. When using mobile payment, users are aware of the need to protect their QR codes to prevent information leakage.

5.3. Limitations and future research directions

This paper designs and builds the mobile payment risk knowledge graph model of policy documents. Although triples can be extracted unsupervised, the noise data cannot extract the required triples well (Carta et al., 2021). It would be helpful to strengthen the study of knowledge graphs and use advanced algorithms for their optimization. We hope to further study the knowledge graph extraction model for all types of texts in the future. In so doing, we will further enhance the impact of the model and the accuracy of knowledge acquisition.

CRediT authorship contribution statement

Huosong Xia: Conceptualization, Supervision, Funding acquisition, Investigation, Methodology, Resources, Validation, Writing – original draft, Writing – review & editing, Project administration. **Yuan Wang:** Formal Analysis, Software, Visualization, Investigation, Writing – original draft, Writing – review & editing. **Jeffrey Gauthier:** Validation, Writing – original draft, Writing – review & editing. **Justin Zuopeng Zhang:** Supervision, Investigation, Validation, Writing – original draft, Writing – review & editing.

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.

Acknowledgment

This research has been supported by the National Natural Science Foundation of China (72171184: Grey private knowledge model of security and trusted BI on the federal learning perspective; 71871172: Model of risk knowledge acquisition and platform governance in FinTech based on deep learning. We deeply appreciate the suggestions from fellow members of Xia's project team and Research Center of Enterprise Decision Support, Key Research Institute of Humanities and Social

Sciences in Universities of Hubei Province (DSS2022).

References

Abu-Salih, B., Al-Tawil, M., Aljarah, I., Faris, H., Wongthongtham, P., Chan, K. Y., & Beheshti, A. (2021). Relational learning analysis of social politics using knowledge graph embedding. *Data Mining and Knowledge Discovery, 35*(4), 1497–1536.

Ahmed, I., Socci, C., Medabesh, A., Severini, F., & Zotti, J. (2021). Economic impact of monetary policy: Focus on real estate sector in Italy. *International Journal of Finance & Economics, 26*(1), 1256–1269.

Ahmed, W., Rasool, A., Javed, A. R., Kumar, N., Gadekallu, T. R., Jalil, Z., & Kryvinska, N. (2021). Security in next generation mobile payment systems: A comprehensive survey. *IEEE Access, 9*, 115932–115950. https://doi.org/10.1109/ACCESS.2021.3105450.doi: 10.1109/ACCESS.2021.3105450

Albashrawi, M., & Motiwalla, L. (2019). Privacy and personalization in continued usage intention of mobile banking: An integrative perspective. *Information Systems Frontiers, 21*(5), 1031–1043.

Al-Emran, M., & Teo, T. (2020). Do knowledge acquisition and knowledge sharing really affect e-learning adoption? An empirical study. *Education and Information Technologies, 25*(3), 1983–1998.

Badgett, A., & Huang, R. (2016). November). Extracting subevents via an effective two-phase approach. In *In Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing* (pp. 906–911).

Bai, T., Li, Y., Wang, Y., & Huang, L. (2021). A Hybrid VAE Based Network Embedding Method for Biomedical Relation Mining. *Neural Processing Letters, 1–12*. https://doi.org/10.1007/s11063-021-10454-5

Brandao-Marques, L., Correa, R., & Sapriza, H. (2020). Government support, regulation, and risk taking in the banking sector. *Journal of Banking & Finance, 112*, Article 105284. https://doi.org/10.1016/j.jbankfin.2018.01.008

Byambasuren, O., Yang, Y., Sui, Z., Dai, D., Chang, B., Li, S., & Zan, H. (2019). Preliminary study on the construction of Chinese medical knowledge graph. *Journal of Chinese Information Processing, 33*(10), 1–9.

Cao, Z., Pan, J., & Li, J. (2020, June). Chinese Sentence Pattern Feature Extraction Based on Massive Data Analysis. In *2020 IEEE International Conference on Artificial Intelligence and Computer Applications (ICAICA)* (pp. 77-81). IEEE.

Carta, S., Ferreira, A., Podda, A. S., Recupero, D. R., & Sanna, A. (2021). Multi-DQN: An ensemble of Deep Q-learning agents for stock market forecasting. *Expert Systems with Applications, 164*, Article 113820. https://doi.org/10.1016/j.eswa.2020.113820

Castro, J. L., Castro-Schez, J. J., & Zurita, J. M. (2001). Use of a fuzzy machine learning technique in the knowledge acquisition process. *Fuzzy Sets and Systems, 123*(3), 307–320.

Chang, V., Chen, W., Xu, Q. A., & Xiong, C. (2021). Towards the Customers' Intention to Use QR Codes in Mobile Payments. *Journal of Global Information Management (JGIM), 29*(6), 1–21. https://doi.org/10.4018/JGIM.20211101.oa37

Chen, H., & Luo, X. (2019). An automatic literature knowledge graph and reasoning network modeling framework based on ontology and natural language processing. *Advanced Engineering Informatics, 42*, Article 100959. https://doi.org/10.1016/j.aei.2019.100959

Chen, M. A., Wu, Q., & Yang, B. (2019). How valuable is FinTech innovation? *The Review of Financial Studies, 32*(5), 2062–2106.

Chen, X., Jia, S., & Xiang, Y. (2020). A review: Knowledge reasoning over knowledge graph. *Expert Systems with Applications, 141*, Article 112948. https://doi.org/10.1016/j.eswa.2019.112948

Choi, H., Park, J., Kim, J., & Jung, Y. (2020). Consumer preferences of attributes of mobile payment services in South Korea. *Telematics and Informatics, 51*, Article 101397. https://doi.org/10.1016/j.tele.2020.101397

Cocosila, M., & Trabelsi, H. (2016). An integrated value-risk investigation of contactless Mobile payments adoption. *Electronic Commerce Research and Applications, 20*, 159–170.

D'Souza, J., & Auer, S. (2021). Sentence, Phrase, and Triple Annotations to Build a Knowledge Graph of Natural Language Processing Contributions—A Trial Dataset. *Journal of Data and Information Science, 6*(3), 6–34.

Das, P., Das, A. K., Nayak, J., Pelusi, D., & Ding, W. (2019). A graph based clustering approach for relation extraction from crime data. *IEEE Access, 7*, 101269–101282.

Dranev, Y., Frolova, K., & Ochirova, E. (2019). The impact of fintech M&A on stock returns. *Research in International Business and Finance, 48*, 353–364.

Du, K. (2018). Complacency, capabilities, and institutional pressure: Understanding financial institutions' participation in the nascent mobile payments ecosystem. *Electronic Markets, 28*(3), 307–319.

Franco-Salvador, M., Gupta, P., Rosso, P., & Banchs, R. E. (2016). Cross-language plagiarism detection over continuous-space-and knowledge graph-based representations of language. *Knowledge-Based Systems, 111*, 87–99.

Gerdes, A. (2020, November). Dialogical guidelines aided by knowledge acquisition: enhancing the design of explainable interfaces and algorithmic accuracy. In *Proceedings of the Future Technologies Conference* (pp. 243-257). Springer, Cham.

Gomber, P., Kauffman, R. J., Parker, C., & Weber, B. W. (2018). On the fintech revolution: Interpreting the forces of innovation, disruption, and transformation in financial services. *Journal of Management Information Systems, 35*(1), 220–265.

Gretzel, U., Fuchs, M., Baggio, R., Hoepken, W., Law, R., Neidhardt, J., … Xiang, Z. (2020). e-Tourism beyond COVID-19: A call for transformative research. *Information Technology & Tourism, 22*(2), 187–203.

Gu, J., Sun, F., Qian, L., & Zhou, G. (2019). Chemical-induced disease relation extraction via attention-based distant supervision. *BMC bioinformatics, 20*(1), 1–14.

Gunnarsson, B. R., Vanden Broucke, S., Baesens, B., Óskarsdóttir, M., & Lemahieu, W. (2021). Deep learning for credit scoring: Do or don't? *European Journal of Operational Research, 295*(1), 292–305.

Guo, Z., Shen, Y., Bashir, A. K., Yu, K., & Lin, J. C. W. (2021). Graph embedding-based intelligent industrial decision for complex sewage treatment processes. *International Journal of Intelligent Systems, 1–19*. https://doi.org/10.1002/int.22540

Hung, W., Tseng, C., Chang, F., & Ho, C. (2021). Effects of Utilitarian and Hedonic Emotion on the Use of Online Banking Services. *Journal of Global Information Management (JGIM), 29*(6), 1–20.

Iman, N. (2018). Is mobile payment still relevant in the fintech era? *Electronic Commerce Research and Applications, 30*, 72–82.

Jansen van Rensburg, S. K. (2021). End-User Perceptions on Information Security: Pragmatic Lessons on Social Engineering Attacks in the Workplace in Gauteng, South Africa. *Journal of Global Information Management (JGIM), 29*(6), 1–16.

Kang, Y., Cai, Z., Tan, C. W., Huang, Q., & Liu, H. (2020). Natural language processing (NLP) in management research: A literature review. *Journal of Management Analytics, 7*(2), 139–172.

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), 1529–1558.

Kumar, V., Ramachandran, D., & Kumar, B. (2021). Influence of new-age technologies on marketing: A research agenda. *Journal of Business Research, 125*, 864–877.

Law, R., Chan, I. C. C., & Wang, L. (2018). A comprehensive review of mobile technology use in hospitality and tourism. *Journal of Hospitality Marketing & Management, 27*(6), 626–648.

Law, R., Leung, D., & Chan, I. C. C. (2019). Progression and development of information and communication technology research in hospitality and tourism: A state-of-the-art review. *International Journal of Contemporary Hospitality Management, 32*(2), 511–534.

Lee, V. H., Hew, J. J., Leong, L. Y., Tan, G. W. H., & Ooi, K. B. (2020). Wearable payment: A deep learning-based dual-stage SEM-ANN analysis. *Expert Systems with Applications, 157*, Article 113477. https://doi.org/10.1016/j.eswa.2020.113477

Lei, Z., Sun, Y., Nanehkaran, Y. A., Yang, S., Islam, M. S., Lei, H., & Zhang, D. (2020). A novel data-driven robust framework based on machine learning and knowledge graph for disease classification. *Future Generation Computer Systems, 102*, 534–548.

Li, F. L., Chen, H., Xu, G., Qiu, T., Ji, F., Zhang, J., & Chen, H. (2020). October). AliMeKG: Domain knowledge graph construction and application in e-commerce. In *In Proceedings of the 29th ACM International Conference on Information & Knowledge Management* (pp. 2581–2588).

Li, P., Mao, K., Xu, Y., Li, Q., & Zhang, J. (2020). Bag-of-Concepts representation for document classification based on automatic knowledge acquisition from probabilistic knowledge base. *Knowledge-Based Systems, 193*, Article 105436. https://doi.org/10.1016/j.knosys.2019.105436

Li, X., Lyu, M., Wang, Z., Chen, C. H., & Zheng, P. (2021). Exploiting knowledge graphs in industrial products and services: A survey of key aspects, challenges, and future perspectives. *Computers in Industry, 129*, Article 103449. https://doi.org/10.1016/j.compind.2021.103449

Li, Z., Tang, H., Xu, X., & Chen, Q. (2019). Knowledge Topic-Structure Exploration for Online Innovative Knowledge Acquisition. *IEEE Transactions on Engineering Management, 68*(6), 1880–1894.

Lim, S. H., Kim, D. J., Hur, Y., & Park, K. (2019). An empirical study of the impacts of perceived security and knowledge on continuous intention to use mobile Fintech payment services. *International Journal of Human-Computer Interaction, 35*(10), 886–898.

Liu, J., Li, X., & Wang, S. (2020). What have we learnt from 10 years of fintech research? a scientometric analysis. *Technological Forecasting and Social Change, 155*, Article 120022. https://doi.org/10.1016/j.techfore.2020.120022

Liu, J., Yang, Y., & He, H. (2020). Multi-level semantic representation enhancement network for relationship extraction. *Neurocomputing, 403*, 282–293.

Liu, S., Yang, H., Li, J., & Kolmanič, S. (2020). Preliminary study on the knowledge graph construction of Chinese ancient history and culture. *Information, 11*(4), 186. https://doi.org/10.3390/info11040186

Liu, Z. (2021). The Impact of Government Policy on Macro Dynamic Innovation of the Creative Industries: Studies of the UK's and China's Animation Sectors. *Journal of Open Innovation: Technology, Market, and Complexity, 7*(3), 168. https://doi.org/10.3390/joitmc7030168

Loh, X. M., Lee, V. H., Tan, G. W. H., Ooi, K. B., & Dwivedi, Y. K. (2020). Switching from cash to mobile payment: What's the hold-up? *Internet Research, 31*(1), 376–399. https://doi.org/10.1108/INTR-04-2020-0175

Lonkani, R., Changchit, C., Klaus, T., & Sampet, J. (2020). A Comparative Study of Trust in Mobile Banking: An Analysis of US and Thai Customers. *Journal of Global Information Management (JGIM), 28*(4), 95–119.

Madureira, A. (2017). Factors that hinder the success of SIM-based mobile NFC service deployments. *Telematics and Informatics, 34*(1), 133–150.

Malaquias, R. F., Malaquias, F. F., Ha, Y. M., & Hwang, Y. (2021). A Cross-Country Study on Intention to Use Mobile Banking: Does Computer Self-Efficacy Matter? *Journal of Global Information Management (JGIM), 29*(2), 102–117.

Mouna, A., & Jarboui, A. (2021). Understanding the link between government cashless policy, digital financial services and socio-demographic characteristics in the MENA countries. *International Journal of Sociology and Social Policy*. https://doi.org/10.1108/IJSSP-12-2020-0544

Nikolopoulos, K., Punia, S., Schäfers, A., Tsinopoulos, C., & Vasilakis, C. (2021). Forecasting and planning during a pandemic: COVID-19 growth rates, supply chain disruptions, and governmental decisions. *European Journal of Operational Research, 290*(1), 99–115.

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*, 404–414.

Omigie, N. O., Zo, H., Ciganek, A. P., & Jarupathirun, S. (2020). Understanding the Continuance of Mobile Financial Services in Kenya: The Roles of Utilitarian, Hedonic, and Personal Values. *Journal of Global Information Management (JGIM), 28*(3), 36–57.

Pal, A., Herath, T., & Rao, H. R. (2021a). Why do people use mobile payment technologies and why would they continue? An examination and implications from India. *Research Policy, 50*(6), Article 104228. https://doi.org/10.1016/j.respol.2021.104228

Pal, A., Herath, T., De, R., & Rao, H. R. (2021b). Is the convenience worth the risk? An investigation of mobile payment usage. *Information systems frontiers, 23*(4), 941–961.

Papadopoulos, D., Papadakis, N., & Litke, A. (2020). A methodology for open information extraction and representation from large scientific corpora: The CORD-19 data exploration use case. *Applied Sciences, 10*(16), 5630. https://doi.org/10.3390/app10165630

Papanikolaou, Y., Roberts, I., & Pierleoni, A. (2019). Deep bidirectional transformers for relation extraction without supervision. *arXiv preprint arXiv:*1911.00313.

Pham, T., Tao, X., Zhang, J., Yong, J., Li, Y., & Xie, H. (2022). Graph-based multi-label disease prediction model learning from medical data and domain knowledge. *Knowledge-Based Systems, 235*, Article 107662. https://doi.org/10.1016/j.knosys.2021.107662

Qasim, H., & Abu-Shanab, E. (2016). Drivers of mobile payment acceptance: The impact of network externalities. *Information Systems Frontiers, 18*(5), 1021–1034.

Qin, B., & Liu, A. (2015). Unsupervised Chinese open entity relation extraction. *Journal of computer research and development, 52*(5), 1029–1035.

Ravat, F., Song, J., Teste, O., & Trojahn, C. (2020). Efficient querying of multidimensional RDF data with aggregates: Comparing NoSQL, RDF and relational data stores. *International Journal of Information Management, 54*, Article 102089. https://doi.org/10.1016/j.ijinfomgt.2020.102089

Roberts, H., Cowls, J., Morley, J., Taddeo, M., Wang, V., & Floridi, L. (2021). The Chinese approach to artificial intelligence: An analysis of policy, ethics, and regulation. *AI & SOCIETY, 36*(1), 59–77.

Ruan, L., Liu, H., & Tsai, S. (2021). XBRL Adoption and Capital Market Information Efficiency. *Journal of Global Information Management (JGIM), 29*(6), 1–18. https://doi.org/10.4018/JGIM.20211101.oa35

Sarhan, I., & Spruit, M. (2021). Open-CyKG: An Open Cyber Threat Intelligence Knowledge Graph. *Knowledge-Based Systems, 233*, Article 107524. https://doi.org/10.1016/j.knosys.2021.107524

Shao, Z., Zhang, L., Li, X., & Guo, Y. (2019). Antecedents of trust and continuance intention in mobile payment platforms: The moderating effect of gender. *Electronic Commerce Research and Applications, 33*(1), 27–56.

Sheng, T. (2021). The effect of Fintech on banks' credit provision to SMEs: Evidence from China. *Finance Research Letters, 39*, Article 101558.

Shi, Y., Xiao, Y., Quan, P., Lei, M., & Niu, L. (2021). Distant supervision relation extraction via adaptive dependency-path and additional knowledge graph supervision. *Neural Networks, 134*, 42–53.

Shih, H., Lai, K., Guo, X., & Cheng, T. C. (2021). Believe It or Not: Employees Intend to Comply With Information Security Policy Because of the Desire for Trade-Offs of ISP Compliance. *Journal of Global Information Management (JGIM), 29*(6), 1–18.

Sommer, M., Figueroa, C., Kwauk, C., Jones, M., & Fyles, N. (2017). Attention to menstrual hygiene management in schools: An analysis of education policy documents in low-and middle-income countries. *International Journal of Educational Development, 57*, 73–82.

Stevenson, M., Mues, C., & Bravo, C. (2021). The value of text for small business default prediction: A deep learning approach. *European Journal of Operational Research, 295*(2), 758–771.

Sun, S., Zhang, F., Liao, K., & Chang, V. (2021). Determine Factors of NFC Mobile Payment Continuous Adoption in Shopping Malls: Evidence From Indonesia. *International Journal of Business Intelligence Research (IJBIR), 12*(2), 1–20.

Sykes, D., Grivas, A., Grover, C., Tobin, R., Sudlow, C., Whiteley, W., … Alex, B. (2021). Comparison of rule-based and neural network models for negation detection in radiology reports. *Natural Language Engineering, 27*(2), 203–224.

Takase, S., Okazaki, N., & Inui, K. (2015, October). Fast and large-scale unsupervised relation extraction. In Proceedings of the 29th Pacific Asia Conference on Language, Information and Computation (pp. 96-105).

Tew, H. T., Tan, G. W. H., Loh, X. M., Lee, V. H., Lim, W. L., & Ooi, K. B. (2021). Tapping the next purchase: Embracing the wave of mobile payment. *Journal of Computer Information Systems, 1–9*. https://doi.org/10.1080/08874417.2020.1858731

Ullah, M. A., Marium, S. M., Begum, S. A., & Dipa, N. S. (2020). An algorithm and method for sentiment analysis using the text and emoticon. *ICT Express, 6*(4), 357–360.

Wamba, S. F., Queiroz, M. M., Blome, C., & Sivarajah, U. (2021). Fostering Financial Inclusion in a Developing Country: Predicting User Acceptance of Mobile Wallets in Cameroon. *Journal of Global Information Management (JGIM), 29*(4), 195–220.

Wang, F., Shan, G. B., Chen, Y., Zheng, X., Wang, H., Mingwei, S., & Haihua, L. (2020). Identity Authentication Security Management in Mobile Payment Systems. *Journal of Global Information Management (JGIM), 28*(1), 189–203.

Wang, Z., Li, L., Zeng, D., & Wu, X. (2021). Incorporating prior knowledge from counterfactuals into knowledge graph reasoning. *Knowledge-Based Systems, 223*, Article 107035. https://doi.org/10.1016/j.knosys.2021.107035

Wang, Z., Xu, S., & Zhu, L. (2018). Semantic relation extraction aware of N-gram features from unstructured biomedical text. *Journal of biomedical informatics, 86*, 59–70.

Wu, Z., Pan, S., Chen, F., Long, G., Zhang, C., & Philip, S. Y. (2020). A comprehensive survey on graph neural networks. *IEEE transactions on neural networks and learning systems, 32*(1), 4–24.

Xia, H., Qingdi, W., & Zhang, Z. (2019). Knowledge heterogeneity in university-industry knowledge transfer: A case analysis of Xu's Ruyi textile. *Knowledge Management Research & Practice, 17*(4), 486–498.

Xu, D., Ruan, C., Korpeoglu, E., Kumar, S., & Achan, K. (2020). January). Product knowledge graph embedding for e-commerce. In *In Proceedings of the 13th international conference on web search and data mining* (pp. 672–680).

Yang, B., & Liao, Y. M. (2021). Research on enterprise risk knowledge graph based on multi-source data fusion. *Neural Computing and Applications*, 1–14.

Yang, Y. J., Xu, B., Hu, J. W., Tong, M., Zhang, P., & Zheng, L. (2018). Accurate and efficient method for constructing domain knowledge graph. *Journal of Software, 29*(10), 2931–2947.

Yeboah, E., Boateng, R., Owusu, A., Afful-Dadzie, E., & Ofori-Amanfo, J. (2020, April). Assessing the Role of Trust in Merchant Adoption of Mobile Payments in Ghana. In *Conference on e-Business, e-Services and e-Society* (pp. 204-215). Springer, Cham.

Yeh, H. (2020). Factors in the ecosystem of mobile payment affecting its use: From the customers' perspective in Taiwan. *Journal of Theoretical and Applied Electronic Commerce Research, 15*(1), 13–29.

Yu, H., Cao, X., Xiao, T., & Yang, Z. (2020). How accurate are policy document mentions? A first look at the role of altmetrics database. *Scientometrics, 125*(2), 1517–1540.

Yu, H., Li, H., Mao, D., & Cai, Q. (2020). A relationship extraction method for domain knowledge graph construction. *World Wide Web, 23*(2), 735–753.

Yu, Q., Liu, K., Yang, Z., Wang, H., & Yang, Z. (2021). Geometrical risk evaluation of the collisions between ships and offshore installations using rule-based Bayesian reasoning. *Reliability Engineering & System Safety, 210*, Article 107474. https://doi.org/10.1016/j.ress.2021.107474

Zhao, S., Zhang, Y., & Wang, X. (2021). Research on syntactic dependency tree and Ontology constraint in remote Supervising relation extraction. *Journal of Physics: Conference Series, 1748*(3), 032–051.

Zhou, T. (2013). An empirical examination of continuance intention of mobile payment services. *Decision Support Systems, 54*, 1085–1091.

Zou, Y., Liu, Y., He, Y., & Wang, Z. (2020, June). Mining of Autism Intervention Methods based on PyLtp Package and TextRank Graph Algorithm. In *2020 IEEE 5th Information Technology and Mechatronics Engineering Conference (ITOEC)* (pp. 609-613). IEEE. doi:10.1109/ITOEC49072.2020.9141696.