Journal of Database Management
Volume 35 • Issue 1 • January-December 2024

The Influence of Readability of Financial App Privacy Policy on Enterprise Performance

Huosong Xia
https://orcid.org/0000-0002-9535-8464
Wuhan Textile University, China

Changlong Xu
Wuhan Textile University, China

Justin Z. Zhang
https://orcid.org/0000-0002-4074-9505
University of North Florida, USA

Sajjad M. Jasimuddin
https://orcid.org/0000-0003-2627-9241
Kedge Business School, France

Xinyu Li
Wuhan Textile University, China

ABSTRACT

From the perspective of the inhibition of privacy computing theory, taking user satisfaction as risk perception, this paper discusses how the readability of financial APP privacy policies inhibits user satisfaction, thus affecting enterprise performance. Firstly, this paper measures the readability of privacy policies by constructing a professional vocabulary and an improved Fog Index formula. Secondly, this paper collects 615 APP privacy policies and corresponding enterprise data and empirically analyzes the impact of the readability of financial APP privacy policies on enterprise performance. This paper enriches research in the field of financial technology and empirically finds that the readability of financial technology APP privacy policies has a negative impact on enterprise performance, while user satisfaction has a positive impact on enterprise performance. In practice, this paper provides a reference for financial technology enterprises to improve the readability of APP privacy policies to improve user satisfaction and enterprise performance.

KEYWORDS

Privacy Protection, Enterprise Performance, Privacy Policy Readability, Text Mining

INTRODUCTION

Because the APP privacy policy is not readable, it is difficult for users to understand. Sometimes, the user's personal information is excessively collected without the user's knowledge, so the user's personal privacy is at risk of being leaked. In order to inform customers how companies collect, use, disclose, and manage their private data, different privacy policies have been implemented. As a unique attribute of financial apps, it requires higher privacy protection. On the one hand, they are the object of providing services and the main body of network information services, so they play a key

DOI: 10.4018/JDM.361999

role in protecting customers' privacy. Among them, the publication and effective implementation of the App privacy policy are effective ways to protect customers' privacy from being leaked. However, at present, there are many problems with the text content and implementation effect of various apps. Some studies have found that consumers generally distrust privacy policies, and most people think that privacy policies are basically ineffective in reflecting law enforcement, changing ideas, or influencing purchase behavior (Zhu et al.,2020).

A privacy policy is a legal contract between users and APP service providers, but some privacy policy texts are very long and unreadable, so many consumers will not read the privacy policies(Georgetown University et al.,2010) and directly agree to the terms of service. However, most privacy policies have disclaimers, personal privacy collected by the APP, and clauses that are unfavorable to users, such as the use and sharing of personal privacy and legal constraints. Users agree to privacy policies without reading them, and they need to face huge potential risks (Chakraborty et al.,2022). For example, the privacy policy unilaterally declares that enterprises have the right to change or stop their business at any time, are compulsory exempt from all responsibilities, and arbitrate for all disputes and arbitration only, etc. This implies the potential risks of personal data privacy disclosure (Zeng et al.,2022); for example, enterprises over-collect users' personal information without customers' knowledge through some unclear privacy policies(Liu et al.,2021), illegally use and disclose users' personal information, and form accurate portraits based on users' use traces and promote advertisements in a targeted manner(Liu et al.,2021). In China, The National Network Information Office reported that Didi Chuxing had over-collected users' personal privacy due to illegal activities and took measures to protect users' private information from further disclosure. Prior to this, many mobile apps were exposed because of the same problem. As a synergy, the platform collects user information and network security risks, and the risk of privacy leakage will increase with the increase of the way the platform collects user information (Ma et al.,2020).

This paper focuses on the privacy policy of financial apps, measures the readability of the privacy policy of financial apps, and provides references when users choose financial apps for financial management. The existing literature has found that users can hardly read the privacy policy of an APP (Ibdah et al.,2021). Many papers discuss whether the privacy policy of an APP is compliant from a legal perspective and put forward relevant solutions. Privacy policies with low readability may also have an impact on corporate performance. These low-readability privacy policies are often obscure and mixed with unfavorable terms for users, which may lead to disputes between users and enterprises, thus affecting users' satisfaction and the performance of enterprises because users' satisfaction will affect the performance of enterprises, showing a positive correlation (Lee et al.,2015). The less readable the privacy policy is, the more unfavorable terms it may contain (Chakraborty et al.,2022), and the user's satisfaction will decrease. Therefore, we can speculate that the readability of privacy policy is related to user satisfaction, which in turn affects enterprise performance. However, previous studies have not explored the potential impact of the readability of privacy policies on corporate performance. Therefore, this paper puts forward the following research questions:

RQ 1: How do we measure the readability of the privacy policy of financial apps?
RQ 2: How does the readability of the privacy policy of financial APPs affect the satisfaction of users and the performance of enterprises?

LITERATURE AND THEORETICAL PERSPECTIVE

Privacy Computing

Privacy computing theory was put forward by R.S. Laufer and M. Wolfe (Margulis et al.,2003). It is an important theory in the field of privacy decision-making, and its core essence is computing.

Privacy computing theory holds that privacy disclosure is influenced by users' calculation of risks and benefits. When users perceive that risks outweigh benefits, they will reduce privacy disclosure; when they perceive that benefits outweigh risks, they will choose to disclose privacy (Sun et al.,2017). Privacy computing theory has become important in studying users' willingness to disclose privacy. In the theory of privacy computing, privacy risk and privacy concern are common variables in building a model. Privacy concerns are intuitive indicators for measuring users' privacy disclosure, and both are cost factors that inhibit users' privacy disclosure. Based on the background of the increasing awareness of users' privacy protection, this paper introduces privacy computing theory from the perspective of risk and cost, takes user satisfaction as risk perception from the perspective of suppression of privacy computing theory, and discusses how the readability of financial APP privacy policy inhibits user satisfaction and further affects enterprise performance.

Privacy Policy

Privacy policies refer to the means by which Internet providers inform users of the types of data they collect and how they handle it (Aïmeur et al.,2016). At present, privacy policies on the market are all standard contracts. In order to maximize their own interests and minimize risks, enterprises will not negotiate with users when making privacy policies and formulate privacy policy terms that are in line with the interests of both parties. Often, these privacy policies will clearly inform the way of collecting, disclosing, and handling users' private information, but they are vague about the use of sensitive information (Soumelidou et al.,2020). Although many countries have formulated relevant laws and regulations to require apps to legally use users' personal privacy, such as the EU's General Data Protection Regulation(Starkbaum et al.,2019), many apps are still reported to contain violations, which may lead to serious privacy leakage. According to the research findings of scholars, it mainly focuses on three aspects. Illegal collection of privacy and secret collecting of user privacy (Luo et al.,2022).

APP did not clearly inform users of the purpose, method, and scope of obtaining and applying privacy data because the description in the privacy policy is relatively broad, and personal privacy is collected against users' wishes, resulting in the illegal collection and abuse of user privacy. Illegal use of privacy and sharing user privacy with third parties (Mutambik et al.,2021). Some apps force users to use targeted push services and personalized commercial advertisements for personal information collected by apps, such as browsing records and search history, with the third parties they cooperate with to achieve targeted marketing. Unreasonable permission claim and forcibly obtaining permission. When installing or running an APP, once the user refuses the current privacy policy, he can't use the services provided by the APP, which seriously infringes on the user's privacy. Some APPs will over-collect the user's privacy; for example, the function provided is to display the calendar, and the app needs to provide location information, which leads to the illegal collection, sharing, and sale of the user's privacy, resulting in serious privacy leakage. The original intention of the privacy policy is to solve users' concerns about privacy risks. However, due to the increasing content and decreasing readability of privacy policies, few people know whether these privacy policies are trustworthy or not and whether there is an illegal collection of users' private information. Therefore, this paper discusses the relationship between the readability of privacy policies of financial apps and user satisfaction and corporate performance from the perspective of readability.

Privacy Policy Readability

The readability of privacy policy is the difficulty of reading and understanding the information conveyed by the text(Crossley et al.,2022). In measuring the readability of privacy policy, most of the existing studies adopt two ways (Liu et al.,2022). The first one is the machine learning method, such as text mining. For example, some scholars cluster texts and calculate the cosine distance between texts to scale readability (Moon et al.,2014). The second is to measure the readability of the privacy policy by using the specific attribute characteristics of the text. This method can usually be divided into two factors: the qualitative dimension of the text (the difficulty of the unit text) and the quantitative dimension of the text (the number of words) (Xu et al.,2022). The machine learning method is more suitable for measuring short texts with heterogeneity and dispersion. Because privacy policies are long text, they are more difficult to read (Ennis et al.,2016), and the effect of using machine learning is not very good. It will be better to measure the readability of the privacy policy by artificially extracting relevant text features. Therefore, this paper measures the readability of privacy policy in a second way.

The first is the dimension of the essence of the text. When people understand a privacy policy, they will examine the three dimensions of words, words, and sentences in the privacy policy (Koonce et al.,2022). If there are more difficult words, vocabulary, and sentences, it is more difficult to understand the privacy policy. There has been related literature to measure the text's readability from three dimensions: words, vocabulary, and sentences. For example, the readability index Fog Index (Li et al.,2016) and Flesh-Kincaid index (Graf et al., 2022; Chua et al.,2017; Jilka et al.,2021; La et al.,2021), where the Fog Index is calculated as shown in Formula 1 and the Flesh-Kincaid Index is calculated as shown in Formula 2.

$$\text{Fog Index} = 0.4*\left(\frac{\text{Number of words}}{\text{Number of sentences}} + 100*\frac{\text{Number of difficult words}}{\text{Number of words}}\right) \tag{1}$$

$$\text{Flesh}-\text{Kincaid Index} = 206.835-1.015*\frac{\text{Number of words}}{\text{Number of sentences}}-0.846*\frac{\text{Number of difficult words}}{\text{Number of words}} \tag{2}$$

These two measures of the readability index divide the text into two levels: sentences and vocabulary. Studies measure the readability of the text by the average length of the sentence and the density of difficult words, respectively (Akgul et al.,2022). There is a difference between Chinese and English texts. The smallest unit of English texts is the letter because letters do not affect the reading quality. For Chinese text, the smallest unit of the text is the word. If there are too many rare words in the text, it will seriously affect readers' reading quality and understanding difficulty. So, should we put the word dimension into the index to measure the readability of the privacy policy? At this time, we need to consider the uniqueness of the privacy policy. Privacy policies belong to a relatively strict and objective partial legal text, which is lengthy and complicated in language (Powell et al.,2018), and the privacy policy of financial APP studied in this paper is more professional, which leads to the fact that this privacy policy generally does not have uncommon words, but is composed of professional vocabulary and long sentences, which affects the readability of privacy policy. Based on this, this paper considers measuring the readability of privacy policy in the "qualitative" dimension from the density of professional vocabulary and the average sentence length.

Then, there is the quantitative dimension of the text. Generally speaking, short texts contain less information and are easier for readers to read, while long texts contain some long and difficult sentences with too much information. Therefore, it is natural to take the size of the privacy policy as an indicator to measure the readability of the privacy policy. Some scholars take the file size of the company's annual report as an indicator to measure its readability (Li et al.,2020), and take the readability as the main variable to study the relationship between the readability of the company's annual report and financing constraints. The results show that the worse the readability of the annual reports is, the higher the financing constraints (Lu et al.,2021). However, when scholars use this variable as an index to measure readability, they often remove the text format because some scholars find that the content of the text is not determined by the text alone but by the pictures and tables in the file (Bonsall et al.,2017), so they need to remove these interference factors. This paper studies the readability of the privacy policy of financial APPs. Generally, the privacy policy of financial APPs is composed of words, and the writing style, logical structure, and text characteristics (bullets, font size, etc.) are similar(Singh et al.,2011). Therefore, this study uses the number of words in the privacy policy to measure the readability of the privacy policy in the "quantity" dimension.

Table 1. Readability indicators and their meanings

Indicator name	Indicator meaning
Professional vocabulary density	The privacy policy number of professional vocabulary divide the total number of words
Average sentence length	The privacy policy total words divided by total sentences
Text length	The natural logarithm of total bytes of text length of the privacy policy
Readability index	Average of standardized scores of professional vocabulary density, average sentence length, and text length

To sum up, this paper uses four different readability indicators to measure the readability of privacy policy. The first is the density of professional vocabulary, using the professional vocabulary in the legal field and the professional vocabulary in the Law of People's Republic of China (PRC) on the Protection of Personal Information, the Network Security Law of the People's Republic of China and the Personal Information Security Code for Information Security Technology (GB/T 35273-2020) to describe the readability at the lexical level. The second is the average sentence length, which uses the total number of words in the privacy policy divided by the total number of sentences to describe the readability at the sentence level. The third is the length of the privacy policy, which uses the natural logarithm of the total bytes of privacy policies to express the readability of the dimension of text volume. The fourth is the improved Fog Index formula, using the average of standardized scores of average sentence length, professional vocabulary density, and privacy policy length. The bigger these four indicators are, the worse the readability of the text is. The standardized formula is as follows:

$$Z = (X - \mu)/\sigma \tag{3}$$

$$Privacy\ policy\ Readability = \sum_{i=1}^{n} Z/N \tag{4}$$

where x is a specific fraction, μ is the mean, and σ is the standard deviation, N represents the total number of samples.

Master Model Construction

The format of the contract adopted by the privacy policy is extremely unfavorable to consumers. When drafting the privacy policy, it is usually the lawyer of the enterprise, or the enterprise invites a third-party company to represent it. As the party of the enterprise, the agent has no motivation to distribute risks fairly, and the monitoring party has no user participation except the enterprise itself. Therefore, the initial goal of making a privacy policy may be to safeguard the enterprise's interests, distort the contract terms, and deviate from the optimal terms of the balance between the enterprise risk and the user risk (Taber et al.,2020). Because of the format contract, these privacy policies are poorly readable and obscure. However, the clauses hidden in it that are unfavorable to users are not easy to find, and finally, disputes are easy to occur, reducing users' satisfaction. Therefore, we can speculate that the less readable the privacy policy is, the more unfavorable the terms to users are, and the lower the users' satisfaction is. There may be two ways of causality: the low readability of privacy policy leads to poor user satisfaction, which may be due to the poor product quality and service quality of APPs. APPs may improve user satisfaction through these obvious measures instead of reducing the readability of privacy policies. Therefore, this paper holds that the less readable the privacy policy is, the lower the user satisfaction may be. Therefore, the following H1 hypothesis is proposed:

H1: The lower the readability of the privacy policy is, the lower the user's satisfaction with the APP is.

Customer satisfaction is an important determinant of customer loyalty, and it is very important to maintain enterprises' market share and profitability (Zaim et al.,2020). According to the discussion in the previous paragraph, if the privacy policy is not readable, the more unfavorable clauses it contains to users, the user's satisfaction may be reduced, which in turn will affect the performance of enterprises.

H2: The less readable the privacy policy is, the worse the performance of the enterprise is.
H3: User satisfaction plays an intermediary role between privacy readability and enterprise performance.

As for the control variables, we selected the enterprise's age, scale, and market share. Some scholars have found that large companies usually improve enterprise performance and customer satisfaction through marketing activities (Coviello et al.,2000) and cultivating loyal users (Lee et al.,2012), and find that enterprise performance is positively related to enterprise scale (Lee et al.,2009). The enterprise scale refers to the number of participants and group members of an enterprise. Generally speaking, if an enterprise has more participants and group members, the scale of the enterprise is greater (Deng et al.,2021). The enterprise age is another important factor that determines enterprise performance and user satisfaction. According to the literature, the profitability of enterprises increases with the age of enterprises (Brown et al.,2003). The aging companies tend to have large profit margins, high productivity, and low debt ratios (Coad et al.,2010). The age of an enterprise is measured by subtracting the establishment time of the enterprise from the current year (Guo et al.,2018). The market share is measured by the percentage of business income to total sales (Li et al.,2022). The existing literature shows that enterprises with high market share have higher enterprise performance, which is an important factor of enterprise performance. Some scholars believe that enterprises with high market share have high dominance and may choose a privacy policy with low readability (Brown et al.,2003), because high dominance can keep the company at a low level of user service (Rego et al.,2013). When users choose enterprise services, they will generally consider the transfer cost, the product quality and service level of substitute enterprises in the same industry, etc., while the product quality and popularity of enterprises with high dominance are the highest, so it is difficult for users to transfer from enterprises to other enterprises. On the one hand, the privacy policies of enterprises with higher market share are less readable, and the terms of service for users are more stringent so that more information can be obtained from users, accurate marketing can be achieved, and users will not be easily transferred. On the other hand, national laws require enterprises to implement more compliant and transparent privacy policies, which will increase the legal cost and reputation costs of enterprises. Considering the cost and user dependence, enterprises with high market share find that they can make profits without strictly abiding by national laws, so their privacy policies will be less readable.

Model Design

In order to test the above hypothesis, this paper uses two Multiple linear regression models to verify. All variables are normalized, changing the influence caused by different dimensions:

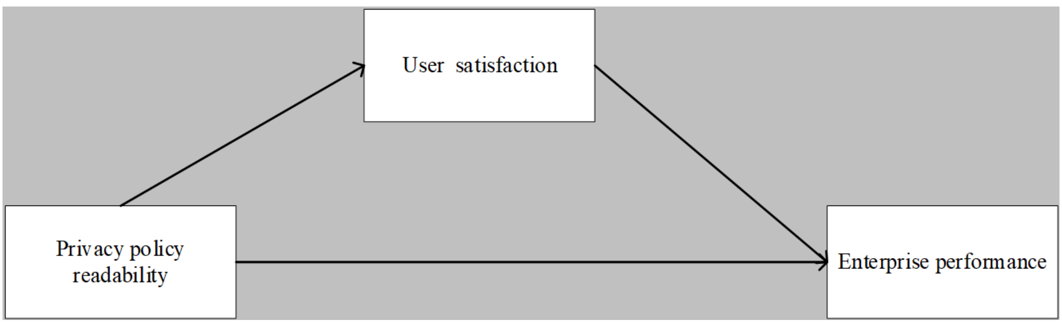
Model 1:

$$\textit{User satisfaction} = \acute{a}_0 + \acute{a}_1 * \mathrm{Pr}\textit{ivacy policy readability} + \acute{a}_2 * \textit{Enterprise size} + \acute{a}_3 * \textit{Enterprise age} + \acute{a}_4 * \textit{Market share} + \acute{a}_5 * \textit{Patent} + \tilde{n}$$

Table 2. Description and measurement of variables

Variable name		Measurement method
Dependent variable (model 1)	User satisfaction	APP score
Dependent variable (model 2)	Enterprise performance	Profitability of enterprises
independent variable	Privacy policy readability	Readability score
Control variable	Enterprise size	Number of participants and group members of enterprises
	Enterprise age	Subtract the establishment time in that year.
	Market share	Registered capital of an enterprise
	Patent	Number of patents

Figure 1.



Model 2:

$$\textit{Enterprise performance} = \hat{a}_0 + \hat{a}_1 * \textit{User satisfaction} + \hat{a}_2 * \textit{Privacy policy readability} + \hat{a}_3 * \textit{Enterprise size} + \hat{a}_4 * \textit{Enterprise age} + \hat{a}_5 * \textit{Market share} + \hat{a}_6 * \textit{Patent} + \tilde{a}$$

DATA AND MASTER MODEL VERIFICATION

Financial APP Privacy Policy Readability Measurement

The data object financial app selected in this paper refers to a mobile app specially designed and used to provide financial services, conduct financial transactions, and manage personal or corporate finances. These applications are typically developed and offered by financial institutions, technology companies, or other financial service providers and are designed to enable users to easily conduct various financial activities such as banking, investment, payments, loan management, wealth management, and more. In this study, we searched the ranking lists of corresponding apps in 2021 on Xiaomi APP Store, Huawei APP Store, and Tencent App Store, respectively, by using the keywords of insurance, stock, fund, bookkeeping, investment, banking, securities, and payment, and found a total of 2,003 financial apps after excluding duplicate results, We downloaded the target apps in batches in February 2022 and obtained their privacy policy. Finance-related applications will typically be categorized as "financial," "finance," etc., while non-finance-related applications may be in other categories. By looking at the app's categories, we excluded 300 pieces of data that were not related to finance and another 203 apps whose privacy policies cannot be viewed or are not Garbled code found or appeared. We finally obtained the privacy policies of 1,342 financial apps.

Table 3. Descriptive analysis of readability of financial APP

variable	N	Mean	Std	Max	Min
Total word count	1342	9.15	0.53	7.03	11.2
Average sentence length	1342	60.27	24.64	13	429
Professional vocabulary density	1342	7.11	2.32	0.16	14.94
Readability index	1342	0.19	0.05	0.01	0.38

Table 4. Readability comparison of 8 categories: insurance, stocks, funds, bookkeeping, investment, banking, securities, and payment

variable	insurance	stock	foundation	bookkeep	investment	bank	securities	payment
Total word count	9.13	9.15	9.23	8.89	9.23	9.27	9.11	9.12
Average sentence length	59.31	57.67	58.08	66.91	60.66	56.36	54.39	59.08
Professional vocabulary density	7.70	6.97	6.72	7.02	7.37	6.51	6.77	6.86
Readability index	0.21	0.19	0.18	0.20	0.20	0.18	0.18	0.19

According to the four indicators of measuring the privacy policy readability of financial apps, that is, professional vocabulary density, average sentence length, readability index, and total bytes of articles, the readability of 1,342 financial apps, including insurance, stocks, funds, bookkeeping, investment, banking, securities, and payment, was analyzed. From the comparison of the readability of 8 categories of insurance, stocks, funds, bookkeeping, investment, banking, securities, and payment, the privacy policies of banking, fund, and securities apps have the best readability (0.18), while those of investment and bookkeeping apps have the worst readability (0.20). There is little difference in the readability of the privacy policies of these eight financial apps. Readability is around 0.19, which is difficult to understand

From the analysis results, the natural logarithm of the total count of financial APP privacy policies is 9.15 (about 10,666 words), the average sentence length is 60.27, and the average professional vocabulary is 7.11 for every 100. After standardization, the overall readability index is 0.19, and the labeling difference is 0.05. In order to make the indicators more comparative and easier to understand the readability of the privacy policy, this paper chose to crawl 401 reports on the epidemic in People's Daily in 2020 as a benchmark for comparing the privacy policies of financial apps. Because the People's Daily, as a newspaper, faces the general public and is relatively readable. However, there is no professional vocabulary for privacy policy in People's Daily. In order to compare the objectivity of the results, the average vocabulary density of financial APP privacy policy is 7.06. The readability of 401 People's Daily articles was measured in the same way. The average natural logarithm of the total count of People's Daily is 7.17 (about 1821 words), and the average sentence length is 43.84. After standardization, the overall readability index is 0.14, and the labeling difference is 0.07. From the comparison results, we can see that the readability indexes of People's Daily are far lower than those of the financial APP privacy policy, so the financial APP privacy policy is still a difficult text with poor readability.

In the previous section, this paper obtains the readability index score of the financial APP privacy policy by text analysis. In this section, we collect more data to discuss the influence of privacy policy readability on user satisfaction and enterprise performance and the intermediary effect of enterprise market share between privacy policy readability and user satisfaction and enterprise performance. The score in the previous section measures the readability of the privacy policy: the lower the readability, the more user-unfriendly terms. User satisfaction is measured by the app store's user rating. In addition,

Table 5. Comparative analysis of privacy policy of financial APP and readability of people's daily

variable	Privacy policy	People's Daily
Total word count	9.18	7.17
Average sentence length	59.71	43.84
Professional vocabulary density	7.06	7.06
Readability index	0.2	0.14

due to the need to measure the performance of enterprises in China, the performance of enterprises can generally be publicly inquired about only by listed companies. Through screening the collected companies, we found that there are only 76 listed companies, and the amount of data is too small. So, we measure enterprise performance by looking for other data. The profitability of an enterprise is influenced by its operating conditions, innovation ability, credit record, organization of Beijing, and enterprise vitality (Sun et al.,2022). QiChaCha can collect information such as its operating conditions, patent information, and credit records. In this paper, the three pieces of information are fused, and then a score of enterprise profitability is obtained by weighting average (Frank et al., 2016). The weights are as follows:

$$r(Enterprise\ performance) = r1 * Business\ condition + r2 * Patent + r3 * credit\ record \tag{5}$$

$$r1 = \frac{x1}{x1 + x2 + x3}$$

$$r2 = \frac{x2}{x1 + x2 + x3}$$

$$r3 = \frac{x3}{x1 + x2 + x3}$$

The higher the profitability score is, the better the performance of the enterprise is, so the performance of the enterprise can be measured by its profitability. The enterprise scale is measured by the number of participants and the number of groups. The age of an enterprise is measured by subtracting the time of establishment from the time of the year. Market share is measured by the registered capital of the enterprise. 615 privacy policies were screened out by the condition that the score was greater than 0, which was used as the research material of this paper. Because the score, registered capital, number of participants, number of groups, number of patents, enterprise age, and readability index are not in the same dimension, this paper adopts a normalized way to unify all variables and cancel the influence of dimensions on the results.

Analysis and Results

Two Multiple linear regression models are used to test Hypothesis 1 and Hypothesis 2, as shown in Table 5.

As can be seen from Table 5, the readability index is significantly related to user satisfaction and enterprise performance ($p<0.001$), and all showed a negative correlation effect. From the data, readability index has a greater impact on user satisfaction than enterprise performance. When the readability index is higher, the privacy policy is obscure to users, and there are too many technical terms, which is not conducive to protecting users' interests. At this time, user satisfaction will be reduced, and corporate performance will also be reduced. In the model, the score is significantly related to enterprise performance, and the readability index increases, which leads to the privacy policy not being easy to read, the user's satisfaction is reduced, and thus the enterprise performance is reduced. Privacy can verify H1 and H2.

Table 5. Influence of readability of privacy policy on enterprise performance

	User satisfaction(H1)	Enterprise performance(H2)
Intercept	-0.467***	-0.064**
grade		0.122***
registered capital	-0.019***	-0.002***
Number of insured persons		
Number of group members		
Number of patents		0.000***
Enterprise age	0.416***	0.354***
Readability index	-0.132***	-0.068***
R_square	0.655	0.465

Note: ***, **, * means passing the significance level test of 1%, 5%, and 10%, respectively, the standard error in brackets, the same below

According to the regression model, among the control variables, the market share measured by registered capital is significantly correlated with user satisfaction and enterprise performance, showing a negative correlation. Because the market share of enterprises is too large, it will cause a monopoly in the industry, and the privacy policies of enterprises with higher market share are less readable, and the terms of service for users are more stringent. National laws require enterprises to implement more compliant and transparent privacy policies, which will increase the legal cost and reputation costs of enterprises. Considering the cost and user dependence, enterprises with high market share find that they can make profits without strictly observing national laws, so the readability of their privacy policies will be lower, which will lead to lower user satisfaction and lower enterprise performance. Regarding the number of patents, users pay more attention to the serviceability of an enterprise when choosing its service, and its innovation ability has little to do with users, so it can be explained that the number of patents has nothing to do with user satisfaction. However, the number of patents is an important indicator of the innovation ability of enterprises, and the innovation ability of enterprises is also an important indicator of their profitability. The higher the number of patents, the stronger enterprises' innovation ability and profitability are. The enterprise age is significantly related to user satisfaction and enterprise performance. The older an enterprise is, the stronger its serviceability and after-sales ability will be. At this time, enterprises choose to keep old users, so user satisfaction is significantly related to the age of the enterprise. The longer an enterprise is, the longer it will survive in the industry, and the larger its users will be, so its operating conditions will be better, and the performance of other enterprises will also be significantly related.

As can be seen from the table, the enterprise scale measured by the number of employees and the number of group members is not related to user satisfaction and enterprise performance. This paper thinks that there may be two reasons. First of all, it may be that the number of participants and the number of group members belong to the private data of enterprises, and there may be some wrong data in the data collected in this paper, which leads to the that the control variable is irrelevant to user satisfaction and enterprise performance. Secondly, theoretically, the number of employees and the number of group members can represent the scale of employees and senior managers. For the manufacturing industry, the larger the scale of employees and senior managers, the greater the output of enterprises and the stronger their profitability. For the financial industry, these two indicators have nothing to do with enterprise performance and may even be a cost to the enterprise. The bigger these two indicators are, the more bloated the enterprise may be, and the efficiency of the daily operation of the enterprise will be reduced, and employees in the financial industry will not come into direct

Table 6. Mediating effect of user satisfaction

	Effect	SE	t	p	LLCI	ULCI
Total effect	-0.0859	0.0296	-2.9001	0.0039	-0.1441	-0.0277
Direct effect	-0.0687	0.0288	-2.3855	0.0174	-0.1252	-0.0121
Indirect effect	-0.0173	0.009			-0.038	-0.002

Table 7. Descriptive statistical results

Variable	Mean	Median	SE	MIN	MAX
User satisfaction	4.248	4.700	1.102	1	5
Enterprise performance	88.491	89	3.219	77	95
Readability	0.201	0.210	0.048	0.030	0.320
Number of insured persons	79879.080	514	727653.321	1	11010101
Number of group members	185.722	70	323.560	2	2241
Enterprise age	5197.541	4685	3354.276	282	14299
Registered capital	899915.668	30000	4374118.285	1	35640625.710
Number of patents	325.615	5	2210.413	1	37129

contact with customers. Therefore, the enterprise scale measured by these two indicators is irrelevant to user satisfaction and enterprise performance.

This paper uses process plug-ins in SPSS26.0 and the Bootstrap method to analyze the intermediary effect of user satisfaction. From Table 6, we can see that there is a direct effect. The direct effect size of user satisfaction between privacy policy richness and corporate performance was -0.0687 (LLCI=-0.1252, ULCI=-0.0121), and the indirect effect size was -0.0173 (LLCI=-0.038, ULCI=-0.002). So, the readability of privacy policies can directly affect the performance of enterprises. Secondly, there are indirect effects, and the readability of privacy policy affects enterprise performance by affecting user satisfaction. According to the results, the direct effect is greater than the indirect effect. Finally, this paper concludes that the mediation effect analysis shows that both direct and indirect effects exist, indicating that user satisfaction plays a partial intermediary role in the readability of privacy policy and enterprise performance, which can verify H3.

The paper uses SPSS statistical analysis software to conduct descriptive statistics on the study variables, including mean, median, standard deviation, and minimum and maximum values, and the results are shown in Table 7. The user satisfaction of different apps varies greatly. The performance of different enterprises is not different, and the data is relatively stable. There are great differences in the richness of privacy policies of different apps, and the overall richness is high. The readability of privacy policies of different apps varies greatly and is generally low.

DISCUSSIONS AND CONCLUSIONS

Theoretical Contributions

This paper innovatively constructs the readability index of financial technology APP privacy policies and empirically tests that the readability of financial technology APP privacy policies and user satisfaction have an impact on enterprise performance. This paper enriches the research in the field of financial technology. Based on the perspective of studying the privacy policy of financial technology APPs, this paper discusses the influence of the readability of privacy policies on enterprise performance and the influence of user satisfaction on enterprise performance, which has certain theoretical marginal contributions:

This paper has built a separate professional vocabulary, which is more targeted. And the Fog Index formula is aimed at English. This paper has improved the financial technology studied in this paper, and the measurement results are more reasonable than the previous literature. The existing research on the readability of the privacy policy of financial technology APPs is as follows. The first one is through machine learning methods such as text mining. For example, some scholars cluster texts and calculate the cosine distance between texts to scale readability. The second is to measure the readability of privacy policies by using the specific attribute characteristics of texts. However, some literature simply counts the number of words and the sentence length to measure the readability of privacy policies or simply uses the Fog Index formula to measure its readability. In this paper, firstly, the professional vocabulary is constructed by using the professional vocabulary in the legal field, the Personal Information Protection Law of the People's Republic of China (PRC), the Network Security Law of the People's Republic of China, and the Personal Information Security Standard of Information Security Technology, and then the Fog Index formula is improved to measure the readability of privacy policies with the average of standardized scores of average sentence length, professional vocabulary density, and privacy policy length.

From the perspective of the readability of financial technology APP privacy policies, this paper explores the impact of the readability of financial technology APP privacy policies on enterprise performance. It is found that the readability of financial technology APP privacy policies has a negative impact on enterprise performance, and user satisfaction has a positive impact on enterprise performance, which improves the related research on financial technology APPs and financial technology enterprise performance and broadens the research perspective in the field of financial technology. In the existing literature, some documents study the readability of APP privacy policy from the general field, and some literature study the influence of online business in the financial field on the performance of financial enterprises. However, there are few pieces of literature to study the readability of the privacy policy of financial technology APPs and then study the influence of the readability of the privacy policy of financial technology APPs on enterprise performance.

Practical Contributions

The research results of this paper have certain practical significance. Through the empirical test, it is concluded that the readability of the privacy policy of financial technology APPs has an impact on enterprise performance. On the basis of this conclusion, we give corresponding suggestions to financial technology enterprises. According to the empirical results, the readability of financial technology APP privacy policies negatively impacts enterprise performance, and user satisfaction positively impacts enterprise performance. Therefore, on the one hand, financial technology enterprises should pay attention to the customization of APP privacy policies, avoid using format contracts, reduce the use of professional vocabulary, shorten privacy policy, avoid using long and difficult sentences in every sentence, and improve the readability of privacy policies. On the other hand, we should pay attention to maintaining user relationships, improving user satisfaction, guiding users to check the APP's privacy policy, and reminding users in bold of the collected user data and the risks users face. When the privacy policy is revised, we should remind users to check it in time to reduce disputes between users and enterprises due to ambiguous privacy policies.

Limitations

There are still some shortcomings in the research, which need to be improved in future research: in the construction of the readability index of the privacy policy of financial technology APPs, although this paper has built a professional vocabulary and improved the Fog Index formula to measure the readability of privacy policies, it is always artificially extracted variables to measure it. Later, deep learning can be introduced to measure the readability of long text privacy policies by improving the unsupervised algorithm to overcome its shortcomings for short texts with heterogeneity and dispersion.

Because most of the enterprises collected in this paper are not listed, we can only indirectly measure the market share and scale of enterprises by collecting some publicly disclosed data, such as the registered capital, the number of participants, and the number of groups. In a future study, we can collect more direct data, such as the turnover data of enterprises, to measure the market share of enterprises more reasonably.

FUNDING STATEMENT

This research has been supported by the National Natural Science Foundation of China (NSFC, 72171184: Grey Private Knowledge model of security and trusted BI on the federal Learning Perspective; NSFC,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, the Research Center of Enterprise Decision Support, and the Key Research Institute of Humanities and Social Sciences in Universities of Hubei Province (DSS20240000).

CONFLICTS OF INTEREST

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

PROCESS DATES

Received: July 10, 2023, Revision: November 9, 2024, Accepted: November 15, 2024

CORRESPONDING AUTHOR

Correspondence should be addressed to Sajjad Jasimuddin; sajjad.jasimuddin@kedgebs.com

REFERENCES

Aïmeur, E., Lawani, O., & Dalkir, K. (2016). When changing the look of privacy policies affects user trust: An experimental study. *Computers in Human Behavior*, *58*, 368–379. DOI: 10.1016/j.chb.2015.11.014

Akgül, Y. (2022). Evaluating the performance of websites from a public value, usability, and readability perspectives: A review of Turkish national government websites. *Universal Access in the Information Society*, 1–16. DOI: 10.1007/s10209-022-00909-4

Alspaugh, T., Scacchi, W., & Asuncion, H.Georgetown University. (2010). Software Licenses in Context: The Challenge of Heterogeneously-Licensed Systems. *Journal of the Association for Information Systems*, *11*(11), 730–755. DOI: 10.17705/1jais.00241

Bonsall, S. B.IV, Leone, A. J., Miller, B. P., & Rennekamp, K. (2017). A plain English measure of financial reporting readability. *Journal of Accounting and Economics*, *63*(2-3), 329–357. DOI: 10.1016/j.jacceco.2017.03.002

Brown, C., & Medoff, J. L. (2003). Firm Age and Wages. *Journal of Labor Economics*, *21*(3), 677–697. DOI: 10.1086/374963

Chakraborty, A., Shankar, R., & Marsden, J. R. (2022). An empirical analysis of consumer-unfriendly E-commerce terms of service agreements: Implications for customer satisfaction and business survival. *Electronic Commerce Research and Applications*, *53*, 101–151. DOI: 10.1016/j.elerap.2022.101151

Chua, H. N., Herbland, A., Wong, S. F., & Chang, Y. (2017). Compliance to personal data protection principles: A study of how organizations frame privacy policy notices. *Telematics and Informatics*, *34*(4), 157–170. DOI: 10.1016/j.tele.2017.01.008

Coad, A. (2010). Exploring the processes of firm growth: Evidence from a vector auto-regression. *Industrial and Corporate Change*, *19*(6), 1677–1703. DOI: 10.1093/icc/dtq018

Coviello, N. E., Brodie, R. J., & Munro, H. J. (2000). An investigation of marketing practice by firm size. *Journal of Business Venturing*, *15*(5-6), 523–545. DOI: 10.1016/S0883-9026(98)00035-4

Crossley, S., Heintz, A., Choi, J. S., Batchelor, J., Karimi, M., & Malatinszky, A. (2022). A large-scaled corpus for assessing text readability. *Behavior Research Methods*, *55*(2), 1–17. DOI: 10.3758/s13428-022-01802-x PMID: 35297016

Deng, X., Huan, L., & Yang, S. (2021). Research on the relationship between enterprise scale, competitive complexity and market performance based on the dual perspectives of static and dynamic-an empirical test from China household appliances industry. [in Chinese]. *Management Review*, *33*(12), 284–294.

Lai Dong, Song Xinbei (2021) Media reports, readability of annual reports of listed companies and financing constraints. journal of management sciences in china. 24(12): 45-61(in Chinese).

Ennis, L., & Wykes, T. (2016). Sense and readability: Participant information sheets for research studies. *The British Journal of Psychiatry*, *208*(2), 189–194. DOI: 10.1192/bjp.bp.114.156687 PMID: 26382948

Frank, M. Z., & Shen, T. (2016). Investment and the weighted average cost of capital. *Journal of Financial Economics*, *119*(2), 300–315. DOI: 10.1016/j.jfineco.2015.09.001

Graf-Vlachy, L. (2022). Is the readability of abstracts decreasing in management research? *Review of Managerial Science*, *16*(4), 1063–1084. DOI: 10.1007/s11846-021-00468-7

Ibdah, D., Lachtar, N., Raparthi, S. M., & Bacha, A. (2021). “Why Should I Read the Privacy Policy, I Just Need the Service”: A Study on Attitudes and Perceptions Toward Privacy Policies. *IEEE Access: Practical Innovations, Open Solutions*, *9*, 166465–166487. DOI: 10.1109/ACCESS.2021.3130086

Jilka, S., Simblett, S., Odoi, C. M., van Bilsen, J., Wieczorek, A., Erturk, S., Wilson, E., Mutepua, M., & Wykes, T. (2021). Terms and conditions apply: Critical issues for readability and jargon in mental health depression apps. *Internet Interventions : the Application of Information Technology in Mental and Behavioural Health*, *25*, 100433–100440. DOI: 10.1016/j.invent.2021.100433 PMID: 34401392

Koonce, L., Leitter, Z., & White, B. (2021). The effect of a warning on investors’ reactions to disclosure readability. *Review of Accounting Studies*, 1–23. DOI: 10.1007/s11142-021-09655-z

LaMonica, H. M., Roberts, A. E., Lee, G. Y., Davenport, T. A., & Hickie, I. B. (2021). Privacy Practices of Health Information Technologies: Privacy Policy Risk Assessment Study and Proposed Guidelines. *Journal of Medical Internet Research*, *23*(9), e26317. DOI: 10.2196/26317 PMID: 34528895

Lee, G. J. (2012). Firm size and the effectiveness of training for customer service. *International Journal of Human Resource Management*, *23*(12), 2597–2613. DOI: 10.1080/09585192.2011.637065

Lee, J. (2009). Does Size Matter in Firm Performance? Evidence from US Public Firms. *International Journal of the Economics of Business*, *16*(2), 189–203. DOI: 10.1080/13571510902917400

Lee, K., Lee, B., & Oh, W. (2015). Thumbs Up, Sales Up? The Contingent Effect of Facebook Likes on Sales Performance in Social Commerce. *Journal of Management Information Systems*, *32*(4), 109–143. DOI: 10.1080/07421222.2015.1138372

Li, Chuntao, & Zhang, Jibao, Natalie. (2020). Readability of Annual Report and Enterprise Innovation. [in Chinese]. *Economic Management.*, *42*(10), 156–173.

Li, D. (2022). Research on the impact of government R&D subsidies on enterprise innovation performance-based on the perspective of enterprise scale and property heterogeneity. [in Chinese]. *Journal of Economics*, *9*(1), 141–161.

Li, X., Zhu, H., & Zuo, L. (2021). Reporting Technologies and Textual Readability: Evidence from the XBRL Mandate. *Information Systems Research*, *32*(3), 1025–1042. DOI: 10.1287/isre.2021.1012

Liu, B., & Sun, W. (2021). Research on the process of mobile users' information disclosure decision-making from the overall perspective of communication privacy management theory. [in Chinese]. *Management Science*, *34*(6), 76–87.

Liu, D., Gao, W., & Min, L. (2022). The influence of readability and attractiveness on commodity sales-a text analysis based on film introduction. [in Chinese]. *China Management Science.*, *30*(6), 167–177. DOI: 10.1007/s11430-020-9838-4

Luo, Q., Yu, Y., Liu, J., & Benslimane, A. (2022). Automatic Detection for Privacy Violations in Android Applications. *IEEE Internet of Things Journal*, *9*(8), 6159–6172. DOI: 10.1109/JIOT.2021.3109785

Ma, C., & Liu, Q. (2020). Privacy Policy Evaluation and Empirical Research of Mobile Health Applications. [in Chinese]. *Library and Information Work.*, *64*(7), 46–55.

Margulis, S. T. (2003). Privacy as a Social Issue and Behavioral Concept. *The Journal of Social Issues*, *59*(2), 243–261. DOI: 10.1111/1540-4560.00063

Moon, S., Park, Y., & Kim, Y. S. (2014). The impact of text product reviews on sales. *European Journal of Marketing*, *48*(11-12), 2176–2197. DOI: 10.1108/EJM-06-2013-0291

Murray, J. Y., Ju, M., & Gao, G. Y. (2012). Foreign Market Entry Timing Revisited: Trade-Off between Market Share Performance and Firm Survival. *Journal of International Marketing*, *20*(3), 50–64. DOI: 10.1509/jim.12.0083

Mutambik, I., Almuqrin, A., Liu, Y., Alhossayin, M., & Qintash, F. H. (2021). Gender Differentials on Information Sharing and Privacy Concerns on Social Networking Sites: Perspectives From Users. *Journal of Global Information Management*, *29*(3), 236–255. DOI: 10.4018/JGIM.2021050110

Powell, A., Singh, P., & Torous, J. (2018). The complexity of mental health app privacy policies: A potential barrier to privacy. *JMIR mHealth and uHealth*, *6*(7), e9871. DOI: 10.2196/mhealth.9871 PMID: 30061090

Rego, L. L., Morgan, N. A., & Fornell, C. (2013). Reexamining the Market Share–Customer Satisfaction Relationship. *Journal of Marketing*, *77*(5), 1–20. DOI: 10.1509/jm.09.0363

Singh, R. I., Sumeeth, M., & Miller, J. (2011). A user-centric evaluation of the readability of privacy policies in popular web sites. *Information Systems Frontiers*, *13*(4), 501–514. DOI: 10.1007/s10796-010-9228-2

Soumelidou, A., & Tsohou, A. (2020). Effects of privacy policy visualization on users' information privacy awareness level: The case of Instagram. *Information Technology & People*, *33*(2), 502–534. DOI: 10.1108/ITP-08-2017-0241

Starkbaum, J., & Felt, U. (2019). Negotiating the reuse of health-data: Research, Big Data, and the European General Data Protection Regulation. *Big Data & Society*, *6*(2), 205–395. DOI: 10.1177/2053951719862594

Sun Xiaoling, Cheng Yang, Zhu Qinghua (2017) Study on the influencing factors of users' behavior intention of privacy disclosure in social search. journal of information. 36(10): 172-179 (in Chinese).

Sun, X., & Yu, Z. (2021). Does profitability affect enterprise R&D decisions? -empirical evidence from listed manufacturing companies in China. [in Chinese]. *Management Review*, *33*(7), 68–80.

Xu Xian, hao yang (2022) Analysis of the readability of financial products from the perspective of consumer protection-based on the measurement and test of the readability of insurance clauses. Insurance Research. (1): 21-32(in Chinese). .DOI: 10.13497/j.cnki.is.2022.01.002

Yu, L., Yi, Z., & Nong, Y. (2022). Personal information security risks of users of network information service platforms and their governance-content analysis based on 117 APP privacy policy texts. [in Chinese]. *Library and Information Work.*, *66*(5), 33–43.

Guo Yue (2018) Signal transmission mechanism of government innovation subsidies and enterprise innovation. China Industrial Economy. (09): 98-116(in Chinese). DOI: 10.19581/j.cnki.ciejournal.2018.09.016

Zaim, H., Ramdani, M., & Haddi, A. (2020) E-CRM success factors as determinants of customer satisfaction rate in retail website. International Journal of Computer Information Systems and Industrial Management Application. 12, 082-092. https://doi-org.hy272.top/10.1108/09564230210447922

Zeng, F., Ye, Q., Yang, Z., Li, J., & Song, Y. A. (2022). Which Privacy Policy Works, Privacy Assurance or Personalization Declaration? An Investigation of Privacy Policies and Privacy Concerns. *Journal of Business Ethics*, *176*(4), 781–798. DOI: 10.1007/s10551-020-04626-x

Zhu, R., Srivastava, A., & Sutanto, J. (2020). Privacy-deprived e-commerce: The efficacy of consumer privacy policies on China's e-commerce websites from a legal perspective. *Information Technology & People*, *33*(6), 1601–1626. DOI: 10.1108/ITP-03-2019-0117

Justin Zhang is a faculty member in the Department of Management at Coggin College of Business in University of North Florida. He received his Ph.D. in Business Administration with a concentration on Management Science and Information Systems from Pennsylvania State University, University Park. His research interests include economics of information systems, knowledge management, electronic business, business process management, information security, and social networking. He has published research articles in various scholarly journals, books, and conference proceedings. He is the editor-in-chief of the Journal of Global Information Management. He also serves as an associate editor and an editorial board member for several other journals.

Sajjad M. Jasimuddin is Professor at the Kedge Business School, France since July 2012. Previously, he taught at Aberystwyth University, Southampton University, King Abdulaziz University, and University of Dhaka. He received MPhil from Judge Business School at Cambridge University (Trinity College), and PhD from Southampton University. He authors 13 chapters and 110 articles, appear in European Journal of Operational Research, Information Systems Journal, Annals of Regional Science, Thunderbird International Business Journal, European Management Journal, Information Systems Management, Journal of Operational Research Society, Industrial Management & Data Systems, Management Decision, Journal of Business & Industrial Marketing, Global Business and Organizational Excellence, International Journal of Organizational Analysis, IJIM, Journal of Management Analytics, Journal of Knowledge Management, JGIM, JIKM, K&PM, IJTHI, EJISE, IRMJ, VINE and KMR&P. Recently, he published a book, Knowledge Management: An Interdisciplinary Perspective (World Scientific, 2012). His research interests are in knowledge management, international business, information management, and strategic management.