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Discovering Company-Specific Key Risk and Success Factors of Music Streaming Subscription Management by Analysing App Store Reviews

A Case Study of Tidal Music Streaming Service

By

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Version of 1

A dissertation submitted in partial fulfilment for the degree of MSc in Business Analytics at Warwick Business School – University of Warwick.

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Executive Summary

Within the intensively competitive global music streaming market, Tidal has been struggling to maintain its own streaming service. Tidal's current financial state became highly vulnerable to the changes in the number of subscribers, as most of its revenue excessively relies on the sales of subscriptions. In order to ensure a stable subscriber base, it is necessary to recognise the current state of the service and construct proper business strategies accordingly. Therefore, this study aims to suggest a framework to diagnose key risk and success factors of Tidal's subscription management by analysing Appstore reviews. Subscription management in this context is defined as managing the streaming service with the goal of retaining existing subscribers while attracting potential subscribers. Based on a review of the literature on key factors of premium subscription and Appstore reviews analysis, this research first collected a total of 104,743 reviews, 10,668 reviews from the Apple App Store and 94,075 reviews from the Google Play Store. Reviews text data were then properly processed for the analysis. The prepared data was then ingested into Structural Topic Modelling (STM) to figure out latent topics within the reviews. The topics are ranked through a ranking model and grouped by their origin (Apple or Google) and direction (Risk or Success). The analysis showed various company-specific key factors that threaten or strengthen the subscription management and each factor has its own characteristics in terms of topic features in the ranking model, which are topic volume, topic polarity, and topic timeliness. Based on these results, practitioners can try various interpretations of the factors and implement a more sophisticated SWOT relevant analysis to set business strategies.

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1 Introduction

1.1 Background

Rank	Company	Market Share
1	Spotify	32%
2	Apple Music	18%
3	Amazon Music	14%
4	Tencent Music	11%
5	YouTube Music	6%
6	Deezer	2%
7	Pandora	1%
8	Others	16%

Table 1.1 Global Music Streaming Subscriptions by Brand Share in 2020 (Mulligan, 2020)

The global music streaming market is becoming more competitive, as most of the major music streaming services like Spotify or Apple Music are increasing their market share aggressively (Lozic, 2020). As shown in table 1.1, Tidal is one of the many companies in 'Others' which only accounts for 16% of the total market share. In order to survive in this harsh business environment, Tidal has tried to keep its niche market with various strategies and its own uniqueness like high-quality audio, music-related articles, and earlier access on tickets to hot concerts and sporting events.

According to the most recent financial report published on 07 Feb 2020 from Tidal's parent Project Panther Bidco (PPB), 97.7% of Tidal's total revenue ($144.3m) in 2018 came from subscriptions (PPB, 2020). This seems mainly because Tidal has no ad-supported freemium policy like Spotify and other effective routes to make revenue apart from its premium service (Tidal, 2020). Unlike Tidal, however, other major companies have alternative monetisation strategies such as selling hardware (speaker) or advertisements. It is a common sense that music streaming services do care about their subscription management, which is the main source to generate revenue. However, it seems even more important especially for Tidal, due to its high revenue dependency (97.7%) on the sale of subscriptions. The high dependency on the sale of subscriptions can indicate that Tidal's future financial state can become extremely vulnerable to the change in the number of subscriptions.

1.2 Research Questions and Aims

This research suggests a framework to analyse app store reviews as one of the diagnostic methods to improve the efficiency of subscription management. Subscription management refers to managing service quality with the goal of retaining existing subscribers while obtaining potential subscribers. The idea to analyse app store reviews came from the fact that the majority of subscribers these days enjoy their music with apps in their electronic mobile devices (Lozic, 2020). As a result, app store reviews that are written based on their own experiences are expected to contain hidden insights on success and risk factors of subscription management.

This research mainly studies what key success and risk factors of subscription management are latent in Apple App Store and Google Play Store reviews by focusing on the following research questions:

Factors indicate topics of app store reviews that are related to subscription management. The following questions will be studied to understand and filter out topics:

- *Topic type*: Which types of topics exist in app store reviews?
- *Topic relevance*: Is topic context relevant and informative enough for subscription management?

Key Factors describe topics that are assumed to significantly threaten (risk factors) or benefit (success factors) the subscription management. In order to scale the level of significance, the following questions will be studied:

- *Topic volume*: How much proportion of a topic is exhibited by reviews?
- *Topic polarity*: How unequally a topic appears on either high or low rating score side? (i.e. Does topic imply explicit sentiment polarity of users?)
- *Topic timeliness*: Does a topic appears more in past time periods or recent time periods?

Using these three topic features, the following questions will be studied to understand the business strengths and weaknesses:

- *Topic ranking*: How important (significant) a topic is in terms of subscription management?
- *Topic direction*: Does a topic affect subscription management negatively or positively?
- *Topic origin*: Does a topic appears more in Apple App Store reviews or Google Play Store reviews?

This research will obtain the top 5 topics per topic direction for each app store, as shown in figure 1.2:

Apple App Store		**Google Play Store**	
Topic Direction		Topic Direction	
-1	+1	-1	+1
Rank 1	Rank 1	Rank 1	Rank 1
Rank 2	Rank 2	Rank 2	Rank 2
Rank 3	Rank 3	Rank 3	Rank 3
Rank 4	Rank 4	Rank 4	Rank 4
Rank 5	Rank 5	Rank 5	Rank 5

Figure 1.2. Expected Research Outcome

The research outcome in figure 1.2 will be interpreted with topic feature scores and domain knowledge to extract the final integrated insights on the key factors. The key factors obtained by this research are believed to directly affect the sale of subscription, revenue, and eventually Tidal's survival. Therefore, this research may be able to attract and inform relevant practitioners and stakeholders who are interested in Tidal's business success. The research approach and results can become a good foundation for their future strategies on subscription management. Although this research implemented a case study only on Tidal, the whole framework of the research can be applied to other streaming services as well. As a result, the research is expected to add some informative points on subscription management across various music streaming services. Those can be considered increasingly important in the industry as the global music streaming market is expanding its size rapidly with a more competitive business environment. Finally, the research can hopefully contribute to other relevant studies in the same academic field or industry.

2 Literature Review

This research will first investigate various factors that can affect customer's intention to pay for premium subscriptions, as Tidal only offers paid subscription streaming services. This research will reference studies not only about the music streaming industry, but also other industries related to the concept of freemium and premium services. In addition, researches about analysing online reviews should be explored, through which various ideas of text analytics approaches are expected to be obtained.

2.1 Key Factors of Premium Subscription

Music Streaming Industry

Mäntymäki, Islam, and Benbasat (2019) discuss the factors that can induce freemium users to upgrade or premium users to stay in the music streaming market. They point out that 'enjoyment' and 'price value' are the key factors that attract freemium users to upgrade, while 'ubiquity' and 'discovery of new content' are the key factors that make premium users stay. Purnamaningsih, Rizkalla, and Erhan (2019) agree that ubiquity and discovery of new content are key factors of music subscription continuance. They detailed that 'ubiquity' and 'personalisation' affect the level of usefulness of streaming service, which in the end makes subscribers more likely to stay and promote the service through word-of-mouth. Danckwerts and Kenning (2019) focus on music-based psychological ownership as a key factor that induces freemium subscribers to upgrade. They argue that a sense of control over accessible music decides the satisfaction level of music-based psychological ownership of subscribers, which is a crucial factor for freemium to premium. Wang, Huang, and Tai (2017) point out that 'perceived ease of use', 'social presence', and 'content richness' are key basis factors affecting the intention of subscription continuance. However, the results can be outdated as the industry has been changed rapidly since 2017.

Meanwhile, Chen, Leon, and Nakayama (2018) broadened the point of view on subscription factors. They emphasise that potential subscribers who do not have a subscription yet should also be considered by dividing factors into two groups, pre-subscription factors driving the purchase of subscription and post-subscription factors driving continuance of subscription. They picked 'social influence' as a key factor that attracts potential customers to subscribe and 'hedonic performance expectancy' as a key factor that induce subscribers to stay. Guerra and Fernandes (2019) add that 'perceived value' and 'perceived fee' of streaming subscriptions are key factors that attract customers to subscribe. They figured out that the impact of the perceived fee is larger than the impact of the perceived value, which implies that customers tend to put more weights on fee-related issues rather than the benefits of services. Li (2019) agrees with Guerra and Fernandes that perceived value affects the intention of subscription but suggests that there is an intermediary factor, 'brand attachment'. He points out that customer experiences perceived by music streaming app decide the level of brand attachment which then eventually affects final purchase intention.

Other Industries

Hamari, Hanner, and Koivisto (2020) studied how perceived value affects the intention of customers to pay for premium service in the freemium game industry. They emphasise that higher 'enjoyment' makes the intention to pay premium service lower while makes the intention to stay with the service higher. This implies that the enjoyment factor can become a risk factor but also a success factor at the same time for Tidal when considering other competitors and its premium-only feature. Bründl (2018) argues that for social content services, enabling co-active behaviour can induce customers to pay for premium options. This provides an idea that the level of interplay between service users can become a crucial factor for premium subscriptions. Rußell (2020) focuses on the importance of 'value discrepancy' between freemium service and premium service for news content providers. He points out that a larger discrepancy ensures more intention for premium service in general. However, the effects of restriction on quantity and choice are sensitive to the total amount of contents. Therefore, it seems important to set an adequate level of value discrepancy according to business circumstance, so that discrepancy factors can be a more effective inducement. Mulligan et al. (2018) constructed a classification model to predict whether a customer will transfer from freemium to premium with various machine learning algorithms. They mainly used features related to the user's level of activeness in using the app. Most of their models achieved significant performance in classification with F-score around 0.9. Although further verification is required for their model, it implies that factors related to user attributes and behaviours in the app should be considered carefully for subscription management.

2.2 Appstore Reviews Analysis

Appstore Reviews

Pagano and Maalej (2013) provide in-depth knowledge of the characteristics of app store reviews. They investigated about 1 million app store reviews to figure out various features. They found that reviews typically have topics about user experience, bug reports, and feature requests. They also found that reviews quality and constructiveness can vary widely. For example, some reviews may contain helpful and innovative ideas while others may only contain simple insulting. Genc-Nayebi and Abran (2017) add that one of the trickiest problems when analysing Appstore reviews is detecting 'opinion spam' and 'fake reviews'. They argue that naïve automated mining of reviews can be dangerous as it does not consider the nature of the reviews. Therefore, it seems important to take app review features into account in order to process and filter out reviews properly before the topic modelling. Sutino and Siahaan (2019) point out that infrequent review topics should also be considered when analysing reviews. This is because those topics can imply key factors but may not be extracted if only frequent topics are analysed. Their research suggests a hint that topic volume is not as important as the other two topic features. Jha and Mahmoud (2019) claim that little attention has been paid for review topics on Non-Functional Requirements (NFRs) of apps in relevant researches. NFRs refer to the high-level requirements that app software should support, such as security, performance, or usability, apart from functional features of an app. They figured out that about 40% out of 6,000 Appstore reviews expressed opinions on at least one type of NFRs and the types differ depending on the app categories. It can be important to be aware of NFR topics during the analysis which may become potential key factors in this research. Meanwhile, Hu, Wang, Bezemer, and Hassan (2018) focus on the consistency of reviews and rating scores of apps that exist across Appstore platforms, called hybrid apps. They investigated 68 hybrid apps in two main platforms Apple App Store and Google Play Store. According to their results, 33 out of 68 apps could not achieve consistent star rating across the platforms and the difference in rating score can be up to three times on the same review topic. The outcome suggests that this research should implement analysis on Appstore reviews which are grouped by its origin.

Review Mining Techniques

Chen et al. (2014) suggest a framework 'AR-Miner' for Appstore reviews mining. They first implemented topic modelling on reviews data and applied a review ranking scheme to identify meaningful topics within the reviews. Daradkeh (2019) introduces a framework that detects salient factors that can affect the adoption of project portfolio management (PPM) software. Like AR-Miner, his approach also applied topic modelling and ranking scheme on online reviews in order to detect the key factors. However, he adopts the technology-organization-environment (TOE) framework in the end, in order to integrate the key factors into the TOE framework. This can enable a clearer understanding of the key factors by reflecting domain-specific theories. This research will adopt the basic idea and flow of these two studies for the foundation of research methodology and customise the required features according to the research objective.

Liu, Du, Sun, and Jiang (2019) point out the limitation of the simple Latent Dirichlet Allocation (LDA) approach which is one of the most common topic modelling techniques. They suggest interactive LDA (iLDA) as an alternative. 'iLDA' is an interactive strategy in which subjective knowledge from domain experts and objective knowledge from LDA can be integrated. This approach ensures high-quality topic and clear meanings of the topic modelling results. Ekinci and İlhan Omurca (2019) agree with the idea that LDA alone may not be efficient enough to obtain high-quality topics. They suggest the 'Concept-LDA' approach which aims to supplement the features of reviews with concepts and named entities through 'Babelfy' software. This enables more accurate detection of latent topics based on not only the co-occurrence of words but also the semantic relevance of words. Their researches warn that simply applying topic modelling techniques on reviews without considering any metadata can result in low-quality topics.

3 Research Methodology

3.1 Data Collection

Data collection refers to preparing target data for data analysis through the ETL process (Kimball et al., 2011). ETL stands for extract, transform, and load. That is, target data should be extracted from web sources, transformed properly for further analysis, and loaded on to the database. This process is crucial as data analysis is impossible without necessary data. Therefore, it is important to construct a well organised ETL process to support efficient data analysis. This research will use Python to build an ETL data pipeline and SQLite as a database.

After investigating the structures of Apple App Store and Google Play Store web pages, this research has found that there is infinite scrolling applied to both pages. That is, it is required to keep scrolling down to see further reviews, otherwise, the page will show only a limited number of reviews. In this case, sending requests for data through API can be an efficient way to scrape all the required review data if possible. Each request will then return a chunk of data as JSON format from the databases of the two app stores directly. The JSON data should be processed and transformed properly according to the database schema so that it can be fit into the metadata of the table to be loaded. The transformed data will be appended to the table This research will scrape all the review data existing in both Appstore.

Before implementing the data collection, the database and 'reviews' table should be created in advance which will store all the required data. As the database will consist of a single table, 'reviews', the database schema is equal to the table metadata. The reviews table metadata is as follows in figure 3.1.1:

reviews
id INT PRIMARY KEY AUTO INCREMENT
username VARCHAR
date DATETIME
rating TINYINT
origin TINYINT
review TEXT

	Dictionary
id	Document (review) ID
username	Username of user who wrote review
date	Date in which review was written
rating	Rating score of review, from 1 to 5
origin	Appstore from which review came Apple = 1, Google = 2
review	review text

Figure 3.1.1. Reviews Table Metadata

After creating the database, the ETL process can be implemented. This research will make two Python scripts, one for Apple App Store ETL (apple.py) and the other for Google App Store ETL (google.py). 'Requests' and 'Google-Play-Scraper' packages are mainly used to construct the two scripts. The outline of the overall data collection process is shown in figure 3.1.2:

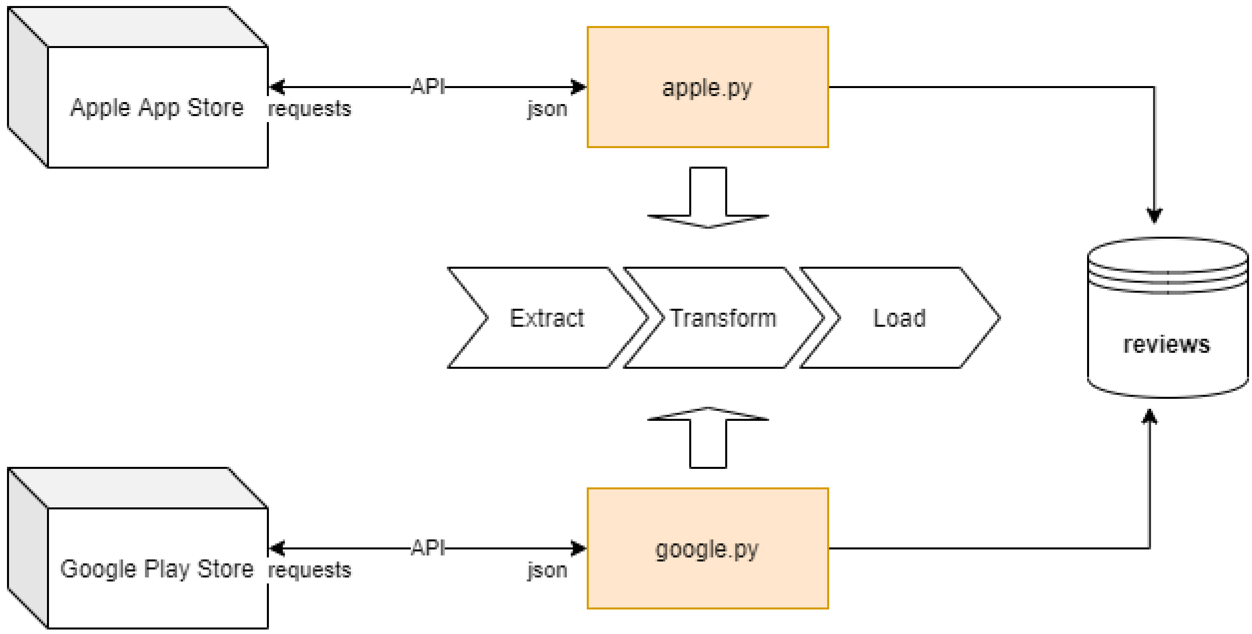

Figure 3.1.2. ETL Process

As a result of the ETL process, this research collected a total of 104,743 reviews. 10,668 reviews are scraped from Apple App Store and 94,075 reviews are scraped from Google App Store.

3.2 Data Preparation

This research will use ‘R’ to clean and prepare the data for analysis. This section covers a variety of techniques on text processing. These techniques are important to ensure credible text analysis results from the review data. Therefore, all review texts should be handled properly before the data analysis part.

3.2.1 Text Cleaning

Text cleaning literally means cleaning unnecessary dirty texts and keep only necessary text data (Agrawal, Paprzycki, and Gupta, 2020). This is crucial in this research, as online reviews are highly informal text documents in general. In order to prevent the result of data analysis to be unbiased, various text cleaning techniques will be tried:

Stop Words

Stop words refer to words which are frequently used in natural language, but hardly have meaning (Silge and Robinson, 2020). Words like “the”, “a”, “she” and “don’t” are an example of stop words. These words need to be removed from the original text data, as they are meaningless disturbing the whole analysis. In addition, it is important to find out and add custom stop words to the existing stop words dictionary. The custom stop words can be found during the whole data preparation or through the Exploratory Data Analysis (EDA) on text data sets. Figure 3.2.1 shows the list of custom stop words that this research has found:

Custom Stop Words

tidal	tidals	music	love	app
apps	lol	yall	tho	def
lot	alot	lover	bit	guy

Figure 3.2.1. Custom Stop Words

Most of these words have been found during the data preparation process. This research will not include competitors' names such as Spotify or Apple Music as stop words, as there could be hidden insights within the reviews mentioning specific competitors. In addition to the custom stop words, repetitive patterns of stop words like 'lolol' or 'hahaha' can also be detected and removed using regex expression. They have a high frequency in the text data but considered to have no meaning for later data analysis. If they are not cleaned properly, the entire analysis result can be biased.

Review Length

Most of the reviews with too short length are less likely to contain meaningful insights in general. The text analysis results can be biased unless those are not dealt with properly. This research decided to drop all the reviews with a length of less than 30. The following table shows a sample of 5 rows from the dropped data:

	id	username	date	rating	origin	review	review length characters
1	1853	user1	2019-12-20	5	1	Quality,quality and quality	27
2	2912	user2	2020-04-11	5	1	Hands down. Really.	20
3	2135	user3	2020-06-11	5	1	Thanks	6
4	2162	user4	2018-08-11	5	1	So much easier to use	21
5	2292	user5	2019-12-12	5	1	I'll give it a 10 thanks tidal	30

Table 3.2.1.a. Reviews with a Length of Less Than 30

As shown in table 3.2.1.a, the reviews hardly contain any meaningful information. Most of the abnormally short reviews were about praising the service with simple exclamations or appreciations.

This implies that these reviews can have a high potential to distort the analysis results making noise during the topic modelling and the ranking model.

Language Processing

This research decided to use only English reviews for more efficient and accurate text analysis. This research will use ‘cld2’ and ‘cld3’ package in R, in order to detect which language a review is written in. In addition to language detection, Unicode should also be handled properly.

	id	username	date	rating	origin	review	review language	review length characters
1	4517	user1	2019-12-22	5	1	𝓣𝓲𝓭𝓪𝓵 𝓲𝓼 𝓪𝔀𝓮𝓼𝓸𝓶𝓮 𝓲 𝓵𝓲𝓼𝓽𝓮𝓷 𝓽𝓸 𝓱𝓲𝓰𝓱 𝓺𝓾𝓲𝓵𝓽𝔂 𝓶𝓾𝓼𝓲𝓬	*NA*	46

Table 3.2.1.b. Review with Unicode

The review in table 3.2.1.b is not written in plain texts but in Unicode. These kinds of reviews should be converted into plain texts first to be processed. This research made a custom normalising function using ‘stringi’ package. This package supports NFC, NFKC, NFD, NFKD, or NFKC_Casefold Unicode normalization.

Word Length

After tokenisation, the review texts will be separated into word tokens. Most of the abnormal length of words amongst them will be malformed or meaningless. These words can hardly be interpreted as plain English and should be removed. Table 3.2.1.c shows some examples of words with a length of over 17 and below 3.

	word	id	n	token length
1	allblackeverything	62615	1	18
2	amaaaaaaazzziiiinnnggg	427	1	21
3	ambientgazeelectro	767	1	18
4	aytkhdvjjvdhjfgfyjgdgkggkhgyifhoufhiutyuuujjjjhhjjjjjjjjjjjjjjjjjjjjjjjjjjjjjjjjhhgbbhhbhh	28475	1	90

	word	id	n	token length
1	a	1753	1	1
2	aa	14479	1	2
3	ab	9138	2	2
4	ac	11388	1	2

Table 3.2.1.c. Words with a Length of over 17 and below 3

However, there could be some domain-related words with a length of 2. For example, words like "ad", "cd" or "dj" should be treated as proper noun words as they are frequently used in the industry. Therefore, this research will keep the words with the length between 3 to 17 plus the domain words with length 2.

Word Join

This is necessary as tokenisation can separate a single word into several pieces. This can be caused by spaces within a single word. For example, some people tend to write “wifi” as “wi-fi” or “wifi” while some tend to write as “wi fi”. The latter will then be separated into two words, wi and fi, after tokenisation. This research figured out “Hifi”, “Wifi” and “Hip-Hop” as possible domain words which can be separated due to tokenisation. These words should be combined properly after the tokenisation using a custom function ‘combine_tokens’ so that they can be dealt with as normal words.

3.2.2 Tokenisation and Lemmatisation

Tokenisation refers to dividing whole review texts into pieces of words (tokens) based on spaces of the review (Silge and Robinson, 2020). This process is important as later analysis will use tokens of reviews, not the entire whole review texts. In addition to the tokenisation, lemmatisation is also necessary. Lemmatisation processes the given set of tokens and transforms the form of tokens into their base form. For example, “driving”, “drove” or “driven” will be all transformed into their base form, “drive”. Lemmatisation ensures a more cohesive set of tokens so that the different forms of words that come from the same root form can be treated as the same words during the analysis. This is reasonable as they have the identical meaning even though the forms are different and the topic modelling clustering algorithm can be sensitive to it. This research used ‘TreeTagger’ engine for lemmatisation.

3.2.3 TF-IDF

Tf-idf stands for Term Frequency-Inverse Document Frequency (Silge and Robinson, 2020). Tf-idf weight is useful to measure the importance of a term within each document in a given corpus. Following is the formula for tf-idf:

$$tf = \frac{Number\ of\ times\ term\ t\ appears\ in\ a\ document}{Total\ number\ of\ terms\ in\ the\ document}$$

$$idf = -\ln\left(\frac{Number\ of\ documents\ with\ term\ t\ in\ it}{Total\ number\ of\ documents}\right)$$
$$= \ln\left(\frac{Total\ number\ of\ documents}{Number\ of\ documents\ with\ term\ t\ in\ it}\right)$$

$$tf\_idf = tf \times idf$$

Term frequency tf measures how frequently a term appears in a document. The more frequent terms can be considered as more important having more weights. Inverse document frequency idf measures how much proportion of documents contains a term and take the inverse value of it. Therefore, idf aims to give a penalty to terms that appear too frequently in most documents and give more weights to rare terms in the corpus. This research will compute tf-idf for the entire corpus in order to trim extremely rare or frequent terms which can add noise to the topic modelling.

3.2.4 Part of Speech (POS) Tagging

POS tagging is the process of detecting part of speech of a word and allocating it to that word (Jockers and Thalken, 2020). This is an important process, as this research will use only noun words for topic modelling. If all texts are used in the topic modelling, non-noun words may add up noise during topic modelling, which can result in messy topic results. Topic modelling with a noun only approach, however, can increase the semantic coherence of the topics. That is, relevant words have better coherence within a topic so that each topic can clearly represent its own exclusive semantic field. This research used 'TreeTagger' engine for POS tagging.

3.2.5 Final Data Modification

Before implementing topic modelling, a final check on the token quality is required (Roberts, Stewart and Tingley, 2019). This is because there could be some missing points in the previous text cleaning process. For example, there could be additional hidden stop words to be removed or tokens that need additional lemmatisation. After the final check, the noun tokens data should be annotated according to their document id. The annotated texts will then be processed by 'textProcessor' function for final text processing. Finally, all the required data which will be ingested into topic modelling should be prepared with 'prepDocuments' function. This includes the data of documents, vocabulary, and metadata. At this stage, this research will keep only the vocabulary that appears at 0.5% of all documents, otherwise, the number of topics can be exaggerated.

3.3 Data Analysis

3.3.1 Structural Topic Modelling (STM)

STM is one of the topic modelling techniques to figure out latent topics under a given corpus (Roberts, Stewart and Tingley, 2019). Unlike other topic modelling techniques, STM utilises metadata which is believed to have an influence on topic prevalence within the corpus to improve the clustering performance. STM is expected to have better performance than other methods in this research. This is because the analysis assumes that topics prevalence can be influenced by metadata of reviews such as rating or date. Especially, the concepts of topic volume, topic polarity, and topic timeliness imply that metadata and topics are highly correlated. This research will use 'stm' package in R. 'stm' package not only enables sophisticated implementation of STM but also various visualisations or evaluations. There are two important settings as an argument for 'stm' function:

prevalence =~ origin + rating + s(date)

The topical prevalence model considers covariates which are believed to influence the frequency with which a topic is exhibited in the corpus. This research assumes that origin, rating score, and date are possible factors. 's()' is for spline function which enables more smooth curve of the time series.

init.type="Spectral" and K=0

This argument enables STM to use the Spectral algorithm introduced in Lee and Mimno (2014) to set an optimal number of topics. This can be an efficient way especially in unsupervised topic modelling situations like this research, as it is difficult to guess how many topics exist in the review corpus.

	t_1	$\cdots$	t_m
d_1	$\theta_{d_1 t_1}$	$\cdots$	$\theta_{d_1 t_m}$
$\vdots$	$\vdots$	$\ddots$	$\vdots$
d_n	$\theta_{d_n t_1}$	$\cdots$	$\theta_{d_n t_m}$

Figure 3.3.1. Document-Topic Loadings Matrix (Chen et al, 2014)

Figure 3.3.1 shows an expected outline of the STM result of document-topic loadings. Each document (review) can consist of various topics with different amounts of loadings. Given n document instances $\mathrm{D} = \{d_1 \dots d_n\}$ and m topics $\mathrm{T} = \{t_1 \dots t_m\}$, $\theta_{d_i t_j}$ $(1 \leq \mathrm{i} \leq \mathrm{n}, 1 \leq \mathrm{j} \leq \mathrm{m})$ represents the proportion (loading) of topic t_j exhibited by document instance d_i. Therefore, $\sum_{j=1}^{m} \theta_{d_i t_j} = 1$. In addition to the document-topic loadings matrix, each topic should be defined and labelled properly. This research will use the 'frex' scoring algorithm for labelling. 'Frex' ensures a more balanced measure of labelling considering both word probability and exclusivity in a topic. Finally, metadata, document-topic loadings matrix, and labelled topics are all prepared to be used in the next part, the ranking model.

3.3.2 Ranking Model

Algorithm 1: Ranking Model

Input: A set of topics T,

feature function set $F = \{f_1, \dots f_n\}$,

feature scores vector set $V = \{v_1, \dots v_n\}$,

$v = \emptyset, \quad \forall v \in V$,

rescale function $RescaleVector(x) = \frac{x - \min(x)}{\max(x) - \min(x)} \times 100$,

and weight vector $W = (w_1, \dots w_n), \ \sum w = 1$

1 for each topic $t \in T$ **do**

2 Compute $f_1(t), \dots f_n(t)$

3 **for** each $f_i(t) \in \{f_1(t), \dots f_n(t)\}$ **do**

4 Append $f_i(t)$ to v_i

5 for each feature scores vector $v \in V$ **do**

6 $v = RescaleVector(v)$

7 for each topic $t \in T$ **do**

8 Let $v_i[t]$ be rescaled score of topic t of feature i, $\quad (i = 1,2, \dots, n)$

9 Set $TopicScore(t) = \sum_{i=1}^{n}(w_i \times v_i[t])$

10 end

Output: Topics in decreasing order of $TopicScore$

Figure 3.3.2. Ranking Model

The ranking model in figure 3.3.2 is designed to compute scores for each topic in T and rank them accordingly. In the algorithm line 1 to 4, the model computes each feature score $f_1(t), \dots f_n(t)$ for each topic $t \in T$ and append those scores to the corresponding vectors $v_1, \dots v_n$. In the algorithm line 5 to 6, the scores in each feature score vector v will be rescaled from 0 to 100. This is because any feature scores in a vector v that exhibits a too large variety of scales will have a dominant effect on the final $TopicScore$, which can eventually bias the topic ranking. After rescaling, each feature will have an equal level of contribution to the $TopicScore$. The $TopicScore(t)$ will then be computed per topic in the algorithm line 7 to 9 having the range of $0 \leq TopicScore(t) \leq 100, \ \forall t \in T$. Higher $TopicScore$ indicates a higher rank.

There are a total of three features in this research case, which are topic volume, topic polarity, and topic timeliness. The following introduces the three feature functions and weights in the ranking model:

Topic volume ($\boldsymbol{f_{Volume}}$) and weight ($\boldsymbol{w_{Volume}}$)

$$f_{Volume}(t) = \sum_{i=1}^{n} \theta_{d_i t}$$

$$w_{Volume} = 0.2$$

$f_{Volume}(t)$ computes the topic volume score of topic t. It represents the total proportion of the topic t in the given set of documents. This research set w_{Volume} as 0.2 as the importance of topic volume is assumed to be less than the other two features. A large volume of a topic may not necessarily mean the topic is crucial. For example, a topic can simply represent general praise on Tidal's service without any specifications, which hardly contain meaningful insights for further service improvement.

Topic polarity ($\boldsymbol{f_{Polarity}}$) and weight ($\boldsymbol{w_{Polarity}}$)

$d_i.R \in \{1,2,3,4,5\}, \qquad (1 \le i \le n): Rating\ Score\ of\ d_i$

$$f_{Polarity}(t) = \left(\frac{\sum_{i=1}^{n} \theta_{d_i t} \times d_i.R}{f_{Volume}(t)} - 3\right)^4$$

$$w_{Polarity} = 0.4$$

$f_{Polarity}(t)$ computes the topic polarity of topic t. $\sum_{i=1}^{n} \theta_{d_i t} \times d_i.R$ indicates the total rating scores of topic t exhibited by all documents. Therefore, $\frac{\sum_{i=1}^{n} \theta_{d_i t} \times d_i.R}{f_{Volume}(t)}$ represents the average rating score of the topic t. $\frac{\sum_{i=1}^{n} \theta_{d_i t} \times d_i.R}{f_{Volume}(t)} - 3$ will then have the range of $-2 \le \frac{\sum_{i=1}^{n} \theta_{d_i t} \times d_i.R}{f_{Volume}(t)} - 3 \le 2$. If the value is closer to either side of -2 or 2, the topic polarity score will be more maximised as it is powered by 4. As a result, a topic with the average rating score closer to the centre of 3 will be underrated while a topic with the average rating score closer to either side of 1 or 5 will be overrated. This idea comes from the assumption that a topic with stronger polarity in the average rating score contains more meaningful insights for subscription management. For example, a topic with an average rating score of 1.2 can be interpreted as subscribers consider the topic highly negatively. It can mean that the Tidal's service may have a significant problem regarding this topic which should be treated with higher priority. In addition to the topic polarity, the topic direction of $+1$ or -1 should be allocated to each topic t according to the sign of $\frac{\sum_{i=1}^{n} \theta_{d_i t} \times d_i.R}{f_{Volume}(t)} - 3$. The topic direction will not be used in the ranking model but will be used later to distinguish whether a topic is a success factor ($+1$) or risk factor (-1). It then becomes possible to rank the topics grouping by topic direction.

Topic timeliness ($f_{Timliness}$) and weight ($w_{Timliness}$)

$TI = [i_0, i_0 + I]: Time\ Interval$

$K = \frac{I}{\Delta i}, \qquad (\Delta i = 1\ month): Total\ Number\ of\ Time\ Windows$

$W_k = [i_0 + (k-1)\Delta i, i_0 + k\Delta i], \qquad (1 \leq k \leq K): k - th\ Time\ Window$

$D_{W_k}: Set\ of\ Documents\ Posted\ in\ W_k$

$v(W_k): Total\ Number\ of\ Documents\ Posted\ in\ W_k, \qquad n = \sum_{k=1}^{K} v(W_k)$

$v(t, W_k) = \sum_{d_i \in D_{W_k}} \theta_{d_i t} : Total\ Number\ of\ Documents\ about\ Topic\ t\ Posted\ in\ W_k$

$p(t, W_k) = \frac{v(t,W_k)}{v(W_k)}: Proportion\ of\ Documents\ about\ Topic\ t\ among\ Documents\ in\ W_k$

$p(t) = \sum_{k=1}^{K} p(t, W_k) : Proportion\ of\ Documents\ about\ Topic\ t\ among\ Documents\ across\ TI$

$l(k) = 2k : Weight\ of\ Freshness\ (Timeliness)$

$$f_{Timliness}(t) = \sum_{k=1}^{K} \frac{p(t, W_k)}{p(t)} \times l(k)$$

$$w_{Timliness} = 0.4$$

$f_{Timliness}(t)$ computes the topic timeliness of topic t. The time interval TI in this research is set as [2014-10-01, 2020-07-01] based on the date range of the reviews data. Therefore, $K = 70$. The main idea of this function is that it puts more weights $l(k)$ on topic proportions $\frac{p(t,W_k)}{p(t)}$ as k increases. This is because this research assumes that a topic which is more likely to appear recently implies up-to-date crucial issues, while a topic that is less likely implies unimportant depreciated issues. Eventually, the topic that appears more in later time windows will have a higher topic timeliness score.

The topic ranking is expected to be different depending on the origin of the reviews. This is because there could be differences in app features such as UX/UI or functionality depending on the Operating System (OS), Android and iOS. Users in the different OS may then have different opinions on the Tidal's service. Therefore, the ranking model will be applied to the two Appstore separately in order to compare and discuss the two ranking results.

4 Results

After all the text processing, a total of 51,459 documents and 215 noun vocabulary were prepared and used in STM. In the metadata, 7,754 documents are from Apple App Store and 43,705 documents are from Google Play Store. According to the STM results, there are a total of 36 topics latent in the review corpus and the details of the topics are shown in appendix 1. The entire topic ranking results are in appendix 2 to 5.

4.1 Key Factors for Apple App Store

Rank	Topic Labels	Volume	Polarity	Direction	Timeliness	Score
1	account_sign_click_log_premium_scroll_email	40.17	40.77	-1	49.19	44.02
2	press_fix_uninstall_galaxy_load_start_update	71.63	1.43	-1	62.95	40.08
3	pause_stop_play_skip_break_phone_button	48.01	3.93	-1	67.71	38.26
4	month_day_cancel_refund_charge_trial_call	89.30	20.86	-1	15.31	32.33
5	playback_message_glitch_issue_time_desktop_network	48.31	0.22	-1	54.60	31.59

Table 4.1.1 Top 5 Topics with Direction '-1' (Apple App Store)

Table 4.1.1 shows the top 5 topics that are believed to affect Tidal's service on Apple App Store in a negative way. Therefore, these top 5 topics are key risk factors of Tidal service on Apple App Store. The following is a summary of the result:

- Highest Topic Volume Score - 89.30 (month_day_cancel_refund_charge_trial_call)
- Highest Topic Polarity Score - 40.77 (account_sign_click_log_premium_scroll_email)
- Highest Topic Timeliness Score - 67.71 (pause_stop_play_skip_break_phone_button)
- Highest Total Score - 44.02 (account_sign_click_log_premium_scroll_email)

Rank	Topic Labels	Volume	Polarity	Direction	Timeliness	Score
1	selection_artist_variety_collection_catalog_choice_release	100.00	80.46	1	38.44	67.56
2	sound_platform_playlist_choice_interface_phone_access	24.93	100.00	1	42.83	62.12
3	limit_genre_quality_world_access_song_playlist	80.11	81.28	1	32.87	61.68
4	stream_access_phone_playlist_interface_version_choice	59.75	78.48	1	36.65	58.00
5	apple_suggestion_user_recommendation_lack_swipe_change	99.65	17.66	1	74.63	56.85

Table 4.1.2 Top 5 Topics with Direction '+1' (Apple App Store)

Table 4.1.2 shows the top 5 topics that are believed to affect Tidal's service on Apple App Store in a positive way. Therefore, these top 5 topics are key success factors of Tidal service on Apple App Store. The following is a summary of the result:

- Highest Topic Volume Score – 100.00 (selection_artist_variety_collection_catalog_choice_release)
- Highest Topic Polarity Score - 100.00 (sound_platform_playlist_choice_interface_phone_access)
- Highest Topic Timeliness Score - 74.63 (apple_suggestion_user_recommendation_lack_swipe_change)
- Highest Total Score - 67.56 (selection_artist_variety_collection_catalog_choice_release)

4.2 Key Factors for Google Play Store

Rank	Topic Labels	Volume	Polarity	Direction	Timeliness	Score
1	pause_stop_play_skip_break_phone_button	77.52	0.00	-1	65.94	41.88
2	account_sign_click_log_premium_scroll_email	27.13	24.10	-1	52.42	36.03
3	customer_week_company_contact_run_response_subscriber	3.67	4.80	-1	51.65	23.32
4	device_times_bug_error_stick_break_phone	16.93	0.55	-1	44.85	21.55
5	month_day_cancel_refund_charge_trial_call	53.04	5.07	-1	18.84	20.17

Table 4.2.1. Top 5 Topics with Direction '-1' (Google Play Store)

Table 4.2.1 shows the top 5 topics that are believed to affect Tidal's service on Google Play Store in a negative way. Therefore, these top 5 topics are key risk factors of Tidal service on Google Play Store. The following is a summary of the result:

- Highest Topic Volume Score – 77.52 (pause_stop_play_skip_break_phone_button)
- Highest Topic Polarity Score - 24.10 (account_sign_click_log_premium_scroll_email)
- Highest Topic Timeliness Score - 65.94 (pause_stop_play_skip_break_phone_button)
- Highest Total Score - 41.88 (pause_stop_play_skip_break_phone_button)

Rank	Topic Labels	Volume	Polarity	Direction	Timeliness	Score
1	limit_genre_quality_world_access_song_playlist	100.00	85.17	1	55.65	76.33
2	selection_artist_variety_collection_catalog_choice_release	90.98	85.42	1	59.88	76.31
3	sound_platform_playlist_choice_interface_phone_access	30.88	100.00	1	63.38	71.53
4	stream_access_phone_playlist_interface_version_choice	51.38	84.63	1	56.10	66.93
5	master_hifi_difference_headphone_library_audiophile_experience	89.86	60.92	1	49.41	62.11

Table 4.2.2. Top 5 Topics with Direction '+1' (Google Play Store)

Table 4.2.2 shows the top 5 topics that are believed to affect Tidal's service on Google Play Store in a positive way. Therefore, these top 5 topics are key success factors of Tidal service on Google Play Store The following is a summary of the result:

- Highest Topic Volume Score – 100.00 (limit_genre_quality_world_access_song_playlist)
- Highest Topic Polarity Score - 100.00 (sound_platform_playlist_choice_interface_phone_access)
- Highest Topic Timeliness Score - 63.38 (sound_platform_playlist_choice_interface_phone_access)
- Highest Total Score - 76.33 (limit_genre_quality_world_access_song_playlist)

5 Discussions

5.1 Interpretation of Results

Key success factors represent the area that Tidal is performing well, which can be understood as strengths of Tidal. On the other hand, key risk factors represent the area that Tidal needs to improve more, which can be understood as weaknesses of Tidal.

Average Score	Key Risk Factors	Key Success Factors
Apple	37.25	61.24
Google	28.59	70.64

Table 5.1. Key Risk Factors VS Key Success Factors

In general, key success factors have higher average scores than key risk factors in both Appstore, as shown in table 5.1. This implies that there seem to be more strengths than weaknesses in Tidal's service, which is a positive signal for the service. In the next two subsections, this research will provide interpretation of the key risk and success factors in the two Appstore based on their topic labels and feature scores results.

5.1.1 Key Risk Factors

Rank	**Apple App Store**	**Google Play Store**
1	Account signing in and logging in	Functionalities for song play
2	App fix and update	Account signing in and logging in
3	Functionalities for song play	Company's response to contacts
4	Cancelling, refund and trial of subscriptions	Bugs and errors with devices
5	Various glitches that occur when using app	Cancelling, refund and trial of subscriptions

Table 5.1.1. Key Risk Factors

Apple App Store

RANK 1. ***Account signing in and logging in***

This topic has the highest total score with the highest polarity score amongst key risk factors. This can mean that the topic is the most crucial risk factor that threatens Tidal's service on the Apple App store and the subscribers may feel highly uncomfortable particularly on account-related issues.

RANK 2. ***App fix and update***

The topic has a relatively high volume and timeliness score. This implies that it can be a newly arising problems and raised frequently by the subscribers recently in the Apple App Store.

RANK 3. ***Functionalities for song play (e.g. pause, stop, play skip or break)***

The topic has the highest timeliness score, which means that it is a newly arising issue these days in the Apple App Store.

RANK 4. ***Cancelling, refund, and trial of subscriptions***

The topic has the highest volume amongst the risk factors and a relatively high polarity but low timeliness score. This can mean that this topic is not an urgent arising issue but rather has been raised in the past in the Apple App Store and the subscribers have highly negative opinions on this issue.

RANK 5. ***Various glitches that occur when using app (e.g. playback or network issues)***

The topic has relatively balanced scores in each feature without any noticeable feature.

Google Play Store

RANK 1. ***Functionalities for song play (pause, stop, play, skip or break)***

The topic has the highest volume, timeliness, and total score amongst the risk factors. This implies that these kinds of functionality issues might the most noticeable problems that occur highly frequently in the Google Play Store service these days.

RANK 2. ***Account signing in and logging in***

The topic shows the highest polarity score amongst the risk factors. Therefore, the subscribers in the Google Play Store may be more likely to have negative emotions, particularly on account-related issue.

RANK 3. ***Company's response to contacts***

The topic generally has relatively balanced scores in each feature without any noticeable feature. This topic has a slightly higher total score than RANK 4 and 5. This is because it has a relatively high topic polarity and timeliness score despite low topic volume score. This implies that a few of the subscribers in the Google Play Store are dissatisfied with the response of Tidal recently when they made a contact.

RANK 4. ***Bugs and errors with devices***

The topic has relatively balanced scores in each feature without any noticeable feature.

RANK 5. ***Cancelling, refund and trial of subscriptions***

The topic has a relatively high volume and polarity scores but low timeliness score. Therefore, many subscribers in the Google Play Store seem to have complaints about this issue in the past.

5.1.2 Key Success Factors

Rank	Apple App Store	Google Play Store
1	Diversity in artists, catalog, collections, and releases	Diversity in genre
2	Sound quality	Diversity in artists, catalog, collections, and releases
3	Diversity in genre	Sound quality
4	User experience on music streaming	User experience on music streaming
5	*Recommendation system*	Tidal Masters and Hi-Fi

Table 5.1.2. Key Success Factors

Apple App Store

RANK 1. ***Diversity in artists, catalog, collections, and releases***

The topic has a full mark in topic volume score with a relatively high topic polarity score. This implies that diversity in these features highly satisfies most of the subscribers in the Apple App Store.

RANK 2. ***Sound quality***

The topic achieved a full mark in the topic polarity score. This can mean that the subscribers in the Apple App Store think the sound quality of Tidal highly positively and most of the reviews with this topic tend to give 5 stars for rating scores.

RANK 3. ***Diversity in genre***

The topic has relatively high topic volume and polarity score. Therefore, many subscribers in Apple App Store may think highly positively about the genre variety of Tidal's service.

RANK 4. ***User experience on music streaming***

The topic has relatively balanced scores in each feature without any noticeable feature. It seems that Tidal is generally providing decent streaming experiences to the subscribers to the Apple App Store subscribers.

RANK 5. ***Recommendation system***

The topic has a high topic volume and timeliness score but a far lower topic polarity score than other topics. Even though the topic has been allocated to the success factors, it can be interpreted more like a risk factor rather than a success factor, due to the low polarity score. Therefore, the topic is marked with asterisks in the table to indicate this special case. That is, the subscribers in Apple App Store may not think the recommendation system as strongly negatively but many of them may want the recommendation system to be more improved recently.

Google Play Store

*RANK 1. **Diversity in genre***

The topic achieved a full mark in topic volume score and relatively high polarity score. This can mean that most of the subscribers in the Google Play Store are satisfied with the genre variety of Tidal's service.

*RANK 2. **Diversity in artists, catalog, collections, and releases***

This topic shows relatively high scores in all three features. This implies that most of the subscribers in the Google Pay Store feel satisfied with the variety of artists, catalog, collections, and releases of the service these days.

*RANK 3. **Sound quality***

The topic has full marks in topic polarity score and the highest timeliness score. This means that the subscribers in the Google Play Store are highly pleased with the sound quality of the service these days.

*RANK 4. **User experience on music streaming***

The topic has a relatively balanced scores in each feature without any noticeable feature.

*RANK 5. **Tidal Masters and Hi-Fi***

The topic has relatively high topic volume score but low timeliness score than other success factors. This implies that most of the subscribers in Google Play Store think Tidal Masters service and Hi-Fi feature in a positive way steadily from the past.

5.2 Diagnosis and Recommendations

The key factors can be divided into two parts, common key factors and unique key factors. Firstly, common key factors can be interpreted as cross-Appstore topics which appear in both origins' top 5. In addition, common key factors tend to have a relatively high rank in both Appstore according to the results. Therefore, these topics are believed to have a higher priority in terms of the significance of influence on the subscribers, as they have global significance on Tidal's subscribers regardless of origins. On the other hand, unique key factors appear in the top 5 of only one side of the Appstore, which implies that they represent partial-Appstore topics that are highly related to one specific origin. Unique key factors are assumed to have less priority than common key factors but exclusive significance in one Appstore. When analysing the results of key factors for subscription management, practitioners should put a higher priority on common key factors that have a larger impact on the entire service across the two Appstore, while focusing on unique key factors to understand what Appstore-specific factors exist.

Risk	Success
Account signing in and logging in	Diversity in artists, catalog, collections, and releases
Functionalities for song play	Sound quality
Cancelling, refund, and trial of subscriptions	Diversity in genre
	User experience on music streaming

Table 5.2.1. Common Key Factors

Table 5.2.1 shows the common key factors for Tidal. 'account signing in and logging in' and 'functionalities for song play' issues have shown high rank in both Appstore. This implies that many Tidal subscribers are highly dissatisfied especially with the problems related to their accounts and functionalities when they play songs. This seems because both issues are technical issues that are directly related to subscribers' app usage. The subscribers can become dissatisfied relatively more easily with this kind of technical issue, which will eventually threaten the sales of subscription significantly. Therefore, Tidal needs to put the highest priority on how to deal with these issues in their service through sophisticated technical development and frequent updates. In addition, 'cancelling, refund, and trial of subscriptions' issue was raised by numerous subscribers in both Appstore the past time, according to the previous interpretation. Especially around 2016, there had been reported many cases that premium account customers who were charged despite their cancelling of subscription (Welch, 2016). In addition, many customers with 30-days free trial had also experienced improper charging even though they had cancelled their trial before 30 days. Most of the customers are highly sensitive to monetary issues in general, which can damage the brand image and eventually, sales of subscriptions severely. Therefore, the subscription management team should put a high priority on inspecting possible root causes within the subscription system and policy in order to prevent this kind of issues to happen again in the future.

On the other hand, Tidal is performing well in the area of common key success factors. Firstly, the subscribers picked diversity in artists, genre, catalog, collections, and releases as one of the most decent features of the service. Especially, Tidal offers a catalog of about 60 million songs including exclusive artists and songs (Tidal, 2020). In addition, it offers a variety of music videos, live concert recordings, and professionally curated playlists. Secondly, the subscribers have been extremely satisfied with sound quality as shown in the interpretation section. This seems mainly because Tidal offers a premium subscription service with high fidelity (Hi-Fi) features that ensure cd-quality music (Tidal, 2020). As a result, the music streaming experience of the subscribers could be more elevated particularly due to these features. These are Tidal's own strengths that differentiate it from other competitors. Therefore, Tidal needs to focus on maintaining and improving these strengths in order to ensure its stable sales of subscription.

Apple App Store		Google Play Store	
Risk	**Success**	**Risk**	**Success**
App fix and update	Recommendation system	Company's response to contacts	Tidal Masters and Hi-Fi
Various glitches that occur when using app		Bugs and errors with devices	

Table 5.2.2. Unique Key Factors

Table 5.2.2 summarises the unique key factors in each Appstore. Subscribers in the Apple App Store are more likely to complain about glitches that occur when using the app and requests for fix and updates. According to the result of this research, they especially have experienced playback issues and network issues. Therefore, the iOS service requires a special inspection of the causes of these problems for quick fix and updates. On the other hand, unlike the Apple App Store, subscribers in the Google Play Store are more likely to complain about bugs and errors related to their devices rather than bugs within the app service. Thus, the Android service seems to require more technical improvement in app compatibility with various android devices. In addition, the subscribers in the Google Play Store were not satisfied with Tidal's improper or late responses when they made a contact. Tidal should be more conscious of providing better feedback or response service to the subscribers in the Google Play Store.

When it comes to unique key success factors, most of the subscribers in the Apple App Store especially care about the recommendation system of Tidal service. Tidal is currently running its own recommendation system called 'My Mix' (Tidal, 2020). As explained in the interpretation part, the subscribers seem to have a somewhat positive sentiment with the current recommendation system but not to be satisfied enough these days. They may recently think that 'My Mix' is lacking some features or has worse performance compared to recommendation algorithms of other competitors such as Apple Music or Spotify. Although this topic is not discussed frequently enough in the Google Play Store reviews, it suggests a new point of view on improvement points to be considered, which can be a breakthrough for further growth in sales of subscriptions. On the other hand, subscribers in the Google Play Store seem to be particularly satisfied with the Tidal Masters service and Hi-Fi feature. Tidal currently offers Hi-Fi as a subscription option that provides the entire catalog with lossless quality audio and a limited catalog with hi-res audio as the name of Tidal Masters (Tidal, 2020). In order to maximise the impact of this strength, Tidal can try to induce subscribers in Apple App Store to experience Hi-Fi features with various advertisements, as they seem less likely to subscribe Hi-Fi according to the results.

5.3 Limitations and Future Work

This research has some limitations in the analysis. Firstly, the gap in the number of reviews extracted from each Appstore can be a potential limitation. This research scraped all the reviews that exist in Appstore in order to contain all the possible reviews in the analysis. However, Apple App Store listed much fewer reviews than Google Play Store. A total of 10,668 and 94,075 reviews were extracted from each Appstore through the ETL process and 7,754 and 43,705 reviews were ingested into the STM respectively. This research did not implement sampling to make an equal number of reviews for both Appstore. This is because this research believed that the gap is not significant, and the impact of the gap can be mitigated in the end by adding origin to the prevalence option in the STM.

However, further verification of this is required in future relevant works by comparing the results with other sampling approaches.

It is difficult to assert that the text cleaning process was flawless, which can be a potential limitation of this research. Even though this research has implemented various techniques to clean the texts of raw reviews, it may still not be enough for the analysis. For example, there could be some important words that should not have been removed or some unnecessary stop words that should have been cleaned properly. In order to improve the text cleaning process, further tries and experimentations with other various possible techniques are required. In addition, more professional domain knowledge can also be helpful to construct a robust set of vocabulary for topic modelling.

The ranking model can also contain a potential limitation. Although the feature functions are reasonably constructed under the logical base of topic modelling theta results, it has a relatively naïve approach and requires further sophisticated adjustments to have more robust results. For instance, in the key success factors of the Apple App Store, the topic 'recommendation system' is allocated to success factors even if it could be interpreted as a risk factor according to its scores and label result. This seems because reviews with a mixture of satisfaction and dissatisfaction or those with not intensive complaints tend to give relatively high rating scores around 4. Then, topics of potential risk factors will be more likely to be misallocated to success factors as the datum point is set at the median rating score of 3. Therefore, this research suggests future works to verify the performance of datum point at around 4 to decide whether a topic is a success factor or risk factor. In addition to this, other adjustments on feature functions or weights should be tried in further studies in order to verify the robustness of the ranking model.

6 Conclusion

By analysing Apple App Store and Google Play Store reviews of Tidal, this research has shown key success and risk factors of the subscription management. This research first properly refined and prepared online reviews data for the analysis through data collection and data preparation stages. Then, this research has implemented STM and applied ranking models on to the prepared data. The research outcome has clearly provided the top 5 risk and success factors for each Appstore. While this research approach limits the generalisability of the results onto the entire music streaming industry, it provides more detailed company-specific factors that few relevant literature have addressed. This research has figured out some insights by inspecting the outcome and the following is the summary of key research findings:

- Tidal subscribers had been highly dissatisfied with refund, cancelling, and trial related problems, but alleviated a lot recently.
- Tidal subscribers have been highly dissatisfied with account signing in and logging in issues.
- Tidal seems to have severe problems these days in their app functionalities related to song play such as pause, stop, skip, start, and break.
- Tidal has provided outstanding service in diversity in artists, genre, catalog, collections, and releases.
- Tidal subscribers have been highly satisfied with their music streaming experiences at Tidal, especially due to the high quality of sound.
- Tidal iOS subscribers have requested for better app fix and updates and improved recommendation system, especially these days.

- Tidal Android subscribers have shown satisfaction in Tidal Masters and Hi-Fi services, but dissatisfaction in Tidal's response to their contacts and app compatibility on Android devices.

Based on these conclusions, practitioners and business stakeholders should consider further SWOT related analysis in order to set business strategies for improved subscription management. Future studies could be possible to apply more sophisticated text processing or topic interpretations if more professional domain knowledge is integrated. In addition, further research is required to verify the robustness of the STM and ranking model.

This research has shown that Tidal's revenue structure relies heavily on the sales of subscriptions due to its unique business characteristics. This is dangerous as their financial state will highly depend on the changes in the number of subscriptions. In order to maintain business competitiveness, Tidal should be aware of the key risk and success factors for their subscription management. However, due to a lack of resources and literature, it was difficult to clearly analyse what specific risk and success factors exist within their service and which factors should have a higher priority compared to other factors. This research has provided a framework to diagnose company-specific risk and success factors and the current state of the service. The final research outcome is expected to become a strong foundation for Tidal's subscription management. Furthermore, the research approach can be adjusted to other music streaming companies or other app-based companies to diagnose their businesses.

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Appendix 1 – Topics

Topic Number	Topic Label	Proportion
1	jay_auto_mqa_care_chromecast_kanye_access	1.47
2	pay_worth_people_cost_quality_access_phone	2.65
3	card_credit_info_payment_purchase_information_call	1.17
4	ability_design_base_option_dope_layout_curate	2.41
5	customer_week_company_contact_run_response_subscriber	1.27
6	money_subscription_price_dollar_deal_idea_break	2.85
7	device_times_bug_error_stick_break_phone	1.78
8	sprint_plan_family_opinion_friend_access_call	1.03
9	google_screen_page_phone_access_break_song	1.32
10	support_home_player_integration_lack_access_phone	1.45
11	wifi_connection_mode_datum_buffer_internet_drop	2.11
12	limit_genre_quality_world_access_song_playlist	5.56
13	list_queue_track_function_stuff_song_break	2.15
14	account_sign_click_log_premium_scroll_email	2.36
15	search_switch_miss_move_title_lyric_itunes	1.98
16	master_hifi_difference_headphone_library_audiophile_experience	5.23
17	playback_message_glitch_issue_time_desktop_network	3.47
18	offline_hour_access_song_phone_break_quality	1.05
19	service_hand_period_application_access_quality_song	3.60
20	press_fix_uninstall_galaxy_load_start_update	4.64
21	spotify_rate_discount_student_life_offer_feature	3.97
22	reason_review_hope_fine_rating_iphone_star	1.39
23	month_day_cancel_refund_charge_trial_call	3.74
24	star_playlist_repeat_button_version_access_phone	4.38
25	album_hiphop_listen_rap_fan_rock_idea	3.86
26	shuffle_download_sort_hate_mix_quality_phone	2.37
27	pause_stop_play_skip_break_phone_button	4.43
28	sound_platform_playlist_choice_interface_phone_access	2.41
29	pandora_radio_youtube_type_functionality_station_access	1.46
30	song_store_phone_break_playlist_star_notice	4.92
31	stream_access_phone_playlist_interface_version_choice	3.47
32	apple_suggestion_user_recommendation_lack_swipe_change	3.30
33	video_content_concert_watch_podcast_ticket_access	2.02
34	selection_artist_variety_collection_catalog_choice_release	5.33
35	crash_complaint_waste_force_minute_freeze_amount	1.44
36	phone_widget_song_quality_break_access_playlist	1.96

Appendix 2 – Topic Ranking (Apple App Store / Risk)

	topic labels	volume	polarity	direction	timeliness	score
1	account_sign_click_log_premium_scroll_email	40.16	40.77	-1	49.19	44.02
2	press_fix_uninstall_galaxy_load_start_update	71.63	1.43	-1	62.95	40.08
3	pause_stop_play_skip_break_phone_button	48.01	3.93	-1	67.71	38.26
4	month_day_cancel_refund_charge_trial_call	89.30	20.86	-1	15.31	32.33
5	playback_message_glitch_issue_time_desktop_network	48.31	0.22	-1	54.60	31.59
6	customer_week_company_contact_run_response_subscriber	17.97	19.11	-1	49.94	31.21
7	reason_review_hope_fine_rating_iphone_star	25.11	0.42	-1	41.83	21.92
8	device_times_bug_error_stick_break_phone	15.37	6.81	-1	39.87	21.75
9	card_credit_info_payment_purchase_information_call	2.69	43.71	-1	9.08	21.66
10	wifi_connection_mode_datum_buffer_internet_drop	19.06	1.06	-1	40.42	20.41
11	google_screen_page_phone_access_break_song	0.01	0.03	-1	50.41	20.18
12	crash_complaint_waste_force_minute_freeze_amount	14.67	7.56	-1	30.32	18.09
13	money_subscription_price_dollar_deal_idea_break	63.67	5.79	-1	1.59	15.68
14	pay_worth_people_cost_quality_access_phone	53.33	0.00	-1	0.00	10.67

Appendix 3 - Topic Ranking (Apple App Store / Success)

	topic labels	volume	polarity	direction	timeliness	score
1	selection_artist_variety_collection_catalog_choice_release	100.00	80.46	1	38.43	67.56
2	sound_platform_playlist_choice_interface_phone_access	24.93	100.00	1	42.83	62.12
3	limit_genre_quality_world_access_song_playlist	80.11	81.28	1	32.87	61.68
4	stream_access_phone_playlist_interface_version_choice	59.75	78.48	1	36.65	58.00
5	apple_suggestion_user_recommendation_lack_swipe_change	99.65	17.66	1	74.63	56.84
6	video_content_concert_watch_podcast_ticket_access	44.87	84.13	1	22.47	51.61
7	star_playlist_repeat_button_version_access_phone	85.05	15.55	1	65.38	49.38
8	master_hifi_difference_headphone_library_audiophile_experience	91.32	50.22	1	27.37	49.30
9	sprint_plan_family_opinion_friend_access_call	5.12	13.68	1	100.00	46.50
10	ability_design_base_option_dope_layout_curate	43.97	42.04	1	51.82	46.34
11	song_store_phone_break_playlist_star_notice	76.57	4.30	1	70.27	45.14
12	service_hand_period_application_access_quality_song	61.91	34.13	1	38.34	41.37
13	spotify_rate_discount_student_life_offer_feature	78.08	27.96	1	35.48	40.99
14	search_switch_miss_move_title_lyric_itunes	35.18	23.21	1	58.39	39.68
15	album_hiphop_listen_rap_fan_rock_idea	82.92	20.12	1	36.25	39.13
16	list_queue_track_function_stuff_song_break	28.68	8.96	1	63.64	34.78
17	shuffle_download_sort_hate_mix_quality_phone	29.67	5.75	1	66.34	34.77
18	pandora_radio_youtube_type_functionality_station_access	15.43	22.43	1	33.24	25.36
19	phone_widget_song_quality_break_access_playlist	21.51	6.40	1	46.01	25.27
20	support_home_player_integration_lack_access_phone	10.30	8.60	1	40.42	21.67
21	jay_auto_mqa_care_chromecast_kanye_access	19.57	14.51	1	23.47	19.11
22	offline_hour_access_song_phone_break_quality	0.00	5.35	1	8.12	5.39

Appendix 4 - Topic Ranking (Google Play Store / Risk)

	topic labels	volume	polarity	direction	timeliness	score
1	pause_stop_play_skip_break_phone_button	77.52	0.00	-1	65.94	41.88
2	account_sign_click_log_premium_scroll_email	27.13	24.10	-1	52.42	36.03
3	customer_week_company_contact_run_response_subscriber	3.67	4.80	-1	51.65	23.32
4	device_times_bug_error_stick_break_phone	16.93	0.54	-1	44.85	21.55
5	month_day_cancel_refund_charge_trial_call	53.04	5.07	-1	18.84	20.17
6	crash_complaint_waste_force_minute_freeze_amount	8.51	0.39	-1	34.16	15.52
7	card_credit_info_payment_purchase_information_call	3.70	28.67	-1	0.00	12.21
8	money_subscription_price_dollar_deal_idea_break	35.28	0.06	-1	10.74	11.38

Appendix 5 - Topic Ranking (Google Play Store / Success)

	topic labels	volume	polarity	direction	timeliness	score
1	limit_genre_quality_world_access_song_playlist	100.00	85.17	1	55.65	76.33
2	selection_artist_variety_collection_catalog_choice_release	90.98	85.42	1	59.88	76.31
3	sound_platform_playlist_choice_interface_phone_access	30.88	100.00	1	63.38	71.53
4	stream_access_phone_playlist_interface_version_choice	51.37	84.63	1	57.00	66.93
5	master_hifi_difference_headphone_library_audiophile_experience	89.86	60.92	1	49.41	62.11
6	video_content_concert_watch_podcast_ticket_access	17.71	86.96	1	40.22	54.42
7	star_playlist_repeat_button_version_access_phone	69.66	25.68	1	72.98	53.40
8	song_store_phone_break_playlist_star_notice	84.82	13.18	1	74.48	52.03
9	ability_design_base_option_dope_layout_curate	27.66	50.96	1	63.56	51.34
10	apple_suggestion_user_recommendation_lack_swipe_change	40.29	28.12	1	79.75	51.21
11	service_hand_period_application_access_quality_song	54.31	45.18	1	52.31	49.86
12	sprint_plan_family_opinion_friend_access_call	0.00	22.25	1	100.00	48.90
13	spotify_rate_discount_student_life_offer_feature	60.69	38.52	1	51.45	48.13
14	search_switch_miss_move_title_lyric_itunes	18.40	34.86	1	67.87	44.77
15	album_hiphop_listen_rap_fan_rock_idea	57.10	33.05	1	48.92	44.21
16	press_fix_uninstall_galaxy_load_start_update	78.59	0.20	1	64.56	41.62
17	list_queue_track_function_stuff_song_break	23.78	19.26	1	69.94	40.43
18	shuffle_download_sort_hate_mix_quality_phone	29.02	13.63	1	71.29	39.78
19	pandora_radio_youtube_type_functionality_station_access	8.80	37.76	1	48.11	36.11
20	playback_message_glitch_issue_time_desktop_network	53.40	1.56	1	59.90	35.27
21	phone_widget_song_quality_break_access_playlist	20.39	15.82	1	54.82	32.34
22	support_home_player_integration_lack_access_phone	9.46	18.01	1	49.53	28.91
23	jay_auto_mqa_care_chromecast_kanye_access	8.27	27.88	1	36.84	27.54
24	google_screen_page_phone_access_break_song	7.96	1.93	1	54.83	24.30
25	wifi_connection_mode_datum_buffer_internet_drop	24.58	0.94	1	44.03	22.90
26	reason_review_hope_fine_rating_iphone_star	5.53	1.20	1	49.74	21.48
27	offline_hour_access_song_phone_break_quality	1.39	16.23	1	24.73	16.66
28	pay_worth_people_cost_quality_access_phone	31.93	3.20	1	14.62	13.52