2021

Utilitarian, Hedonic and Monetary Motivations of Using Mobile Learning Apps: Opinion Mining Using Big Data Text Analytics

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Full research paper

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Abstract

Mobile learning sheds light on the educational benefits of using mobile devices for learning since it is flexible, taking place across contexts, time, subjects, people, and technologies. The challenge of making a sustainable interlock between users and a learning app could be tackled by studying online reviews written by real users of learning apps. Using this relatively untapped source of information, this study aims to understand the utilitarian, hedonic, and monetary motivations of users. This study aims to develop a methodological framework for capturing the Perceived Usefulness, Perceived Enjoyment, and Perceived Cost construct from big text data and test the relationship of these constructs with User Satisfaction. We collect the reviews of four learning apps with different learning content: second language, programming, music, and brain training. The findings of this study move the literature forward by illustrating motivations for using learning apps and how they may impact user satisfaction.

Keywords: Mobile Learning, User Satisfaction, Perceived Usefulness, Perceived Enjoyment, Perceived Cost

1 Introduction

In the last decade, mobile devices have spread at an unprecedented rate, and 95 percent of the world's population now lives in an area covered by a mobile-cellular network (Crompton et al., 2018). Besides, mobile technologies have recently been seen as a wide-ranging educational application that provides users with customized information, adaptive support, and rapid social engagement platforms (Sharples, 2015; Song & Kong, 2017). Due to its wide range of value-adding features, mobile technology has advanced enough to offer engaging learning activities and support learning environments where individuals can enjoy learning wherever and whenever they want (Cheon et al., 2012). The majority of adults own multiple mobile devices, indicating that gadget ownership has skyrocketed. 18–29-year-olds are the most incredible group of mobile device users, which is also the age range of college students (Crompton et al., 2018).

The term "mobile learning" refers to learning that takes place on a mobile device. “Learning in many contexts, through social and content exchanges, while using personal electronic devices” is how the word is wholly defined (Crompton et al., 2018; Laurillard, 2007). This concept sheds light on the educational benefits of using mobile devices for learning since it is untethered, taking place across contexts, time, subjects, people, and technologies (Laurillard, 2007; Traxler, 2009; Traxler, 2010). Most importantly, mobile learning enables users to learn with no time and location restrictions in formal and informal educational settings (Almaiah & Man, 2016).

A growing number of countries are advocating government-funded initiatives to encourage schools to include mobile technology into their regular curriculum (Hwang et al., 2018; Lai, 2020). This makes this field of study worth the attention of scholars to use various ways to analyze data collected from users to study and advance this field. According to O'Brien and Cairns (2016), educational researchers' objective is to provide learning environments for learners to shape their behavior by motivating them to engage and get involved more in learning activities. Mobile technologies have piqued the interest of educators and academics since they can serve this goal by providing learners with various experiences, encouraging them to engage in activities that create value and satisfaction (Kim et al., 2013). In the post-adoption period, the challenge of making a sustainable interlock between users and the system must be addressed to guide practitioners to design a thriving mobile learning environment.

The use of educational apps among individuals for informal learning is voluntary, and such apps are popular among a wide range of demographics. Besides, users’ needs evolve from time to time and vary across different apps with different designs and learning content. Therefore, businesses in this field should be mindful of the evolving nature of customer needs and use a holistic approach to retain their competitive position and prioritize dynamic customer needs. The challenge of designing a user-centered mobile learning environment in a data-driven way could be tackled by using user-generated content in the form of online reviews. Big textual data has proven to be a valuable source of information since it is timely, reliable, concise, and has the potential to be automatically analyzed to enhance the decision support systems (Jeong et al., 2019; Joo et al., 2020; Lee & Sohn, 2019; Nan & Lu, 2014; Palese & Usai, 2018; Pröllochs et al., 2020; Symitsi et al., 2020). Using this relatively untapped source of information, this study aims to understand different motivations for using mobile learning apps among users: utilitarian, hedonic, and monetary.

Thus, the research questions that motivate this study are:

RQ 1. How do users express their utilitarian, hedonic, and monetary motivations for using a mobile learning app through online reviews?

RQ 2. How can we capture the Perceived Usefulness, Perceived Enjoyment, and Perceived Cost construct from online reviews?

RQ 3. Is there a significant association with the level of PU, PE, and PC in reviews to User Satisfaction (star rating)?

Firstly, we will use an unsupervised topic modeling technique to explore the emergent topics of reviews and analyze the topics related to the mentioned motives. The typical patterns of writing a review among users will be developed through a qualitative study of frequent and exclusive keywords of each related topic. The output of this phase will be used to generate semi-supervised topic models categorizing the reviews of a learning app into four clusters. Three of the clusters will be designated for the different motivations of using a learning app, and the rest of the reviews will be placed in the fourth topic. Secondly, we will use this semi-supervised topic model to measure the level of Perceived Usefulness, Perceived Enjoyment, and Perceived Cost of each review. In other words, each review will have loading values showing the relevance of its textual content to the constructs mentioned above. Third, we will use regression analysis to see if the level of PU, PE, and PC reviews is significantly related to the level of User Satisfaction. Users express their satisfaction through positive or negative online reviews by stating what issues lead to dissatisfaction and what aspects of the app keep them satisfied and engaged.

Figure 1 shows the proposed research model of this study. We have divvied the motivations of using a mobile learning app into three categories: Utilitarian, Hedonic, and Monetary. The corresponding constructs for each category of motives are defined from the theory: Perceived Usefulness, Perceived Enjoyment, and Perceived Cost. In addition to these constructs, we aim to control the impact of the length of the reviews and the version of the app on the satisfaction level of users. Users may show a different level of satisfaction due to significant changes in the new updates of the app. Besides, satisfied users may write reviews lengthier or shorter than dissatisfied users. Therefore, we need to include Review Length and App Version as two control variables in the proposed model to ensure the variability of the User Satisfaction is not caused by them.

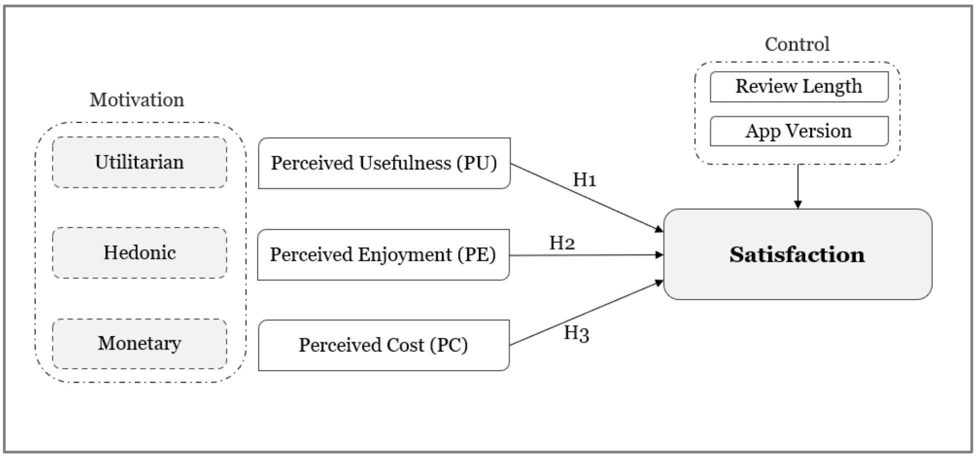

Figure 1: Research model

The main contribution of this study is twofold. First, we validate the developed hypotheses based on Electronic Word of Mouth (e-WOM) as the previous research mainly has validated these relationships based on the collated data through a questionnaire. This study uses unstructured data to measure three different motives for using a learning app from users' perspectives. Second, we develop a methodological framework for generating the Perceived Usefulness, Perceived Enjoyment, and Perceived Cost construct from reviews written by real users. Using big unstructured data as a value of the source of information requires a rigorous methodological framework to generate the measurable constructs from the textual data. This study will attempt toward this goal.

This article's organization is as follows: Section 2 discusses the research design, data collection strategy, and the methodological framework of this paper. This section will be followed by analyzing the findings. The concluding remarks, including the contributions, implications, and limitations of this study, as well as the future works, are then presented.

2 Methodology

Since it is considered a systematic extraction of knowledge from data, machine learning has piqued the interest of academics from numerous fields (Agarwal & Dhar, 2014). We require scientific procedures to transform raw data into useful information, which is an essential component of research-related resources. In other words, machine learning has been defined as the systematic extraction of real-world but not evident or observable patterns and information from raw data (Dhar, 2013). In this section, we first present the research design of this study and then explain the data collection strategy chosen for the goals of this study. Then, we will present the topic modeling techniques we use to transform raw data of online review into a set of latent topics.

Figure 1 shows the methodological approach of this study in three steps. The first step is called exploratory, where we extract the online reviews from Google Play. After cleaning the data, we will use unsupervised topic modeling by applying the LDA algorithm to explore the emergent topics in the online reviews written by users. We will compute three sets of words for each cluster: most frequent, most exclusive, and more indicative and find the most representative words for Perceived Usefulness, Perceived Enjoyment, and Perceived Cost constructs. Using the representative keywords as the seed words, in the second stage, we generate the guided topics of reviews to categorize the reviews into four groups: Utilitarian, Hedonic, Monetary, and Unknown. The 'Unknown cluster is where the irrelevant reviews to our study will reside. The next step in our framework is called 'Confirmatory.' In this step, we generate the loading of each review to different universal topics and test the proposed research model by findings the association of each construct to User Satisfaction. We then re-test the same model with new data from different apps to test the robustness of the generated model from the previous stage.

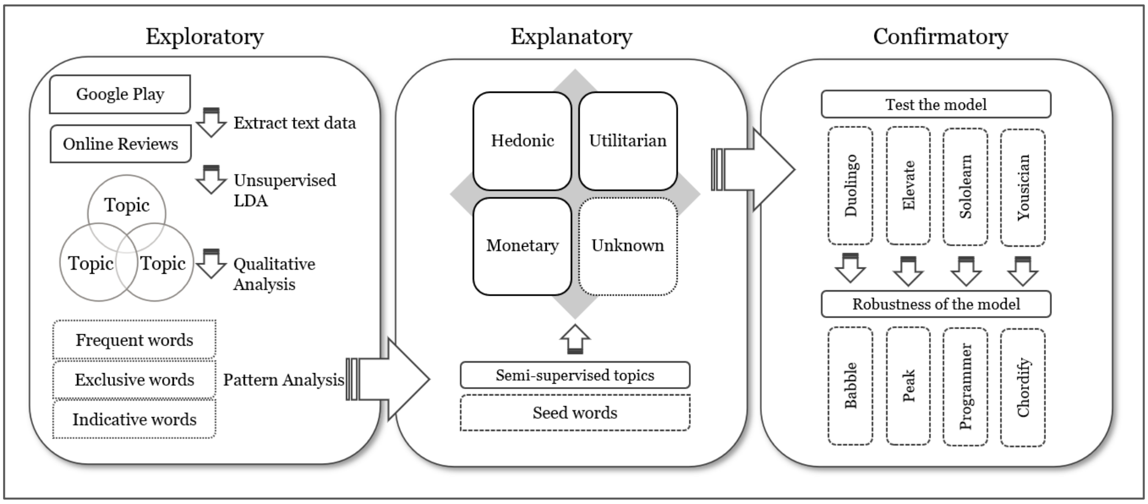

Figure 1. The methodological approach of this study in three steps

2.1 Data Collection

Being one of the most popular marketplaces for mobile apps, Google Play allows users to express themselves through reviews and ratings. Users can express their feelings, attitudes, and experiences and how satisfied they are with a particular app. User reviews of mobile applications on the internet provide helpful information for user experience researchers and educational technology designers. In this study, we want to look at user reviews as the "voice of the users" and find out what they care about. To create an initial dataset of raw data, we will extract the online reviews of four different apps with different learning content: Duolingo, Elevate, SoloLearn, and Yousician. We will also extract the reviews of their competitors in the market: Babble, Peak, Programming Hub, and Chordify. Table 1 presents the description of each application and the number of reviews to be analyzed. It's worth noting that the number of reviews shown in this table indicates the final set of reviews after pre-processing the text data to clean the outliers, noisy, and incomplete text data.

Mobile App	Learning Content	Description	Reviews
Main Apps			
Duolingo	Second language	*"To practice speaking, reading, listening, and writing to build your vocabulary and grammar skills."*	41,335
Elevate	Brain training	*"To improve attention, speaking skills, processing speed, memory, math skills, and more."*	24,266
SoloLearn	Programming	*"To learn coding concepts, programming knowledge, and effective coder skill."*	9,210
Yousician	Music	*"To learn, play and master the Piano, Guitar, Bass, Ukulele, or Singing / Vocals."*	14,131
Equivalent apps in the market			
Babble	Second language	*"To learn a language with a variety of learning methods including regular lessons, speech recognition, podcasts & more."*	3,123
Peak	Brain training	*"Peak uses brain games and puzzles to challenge memory, language, and critical thinking to keep your mind active."*	4,340
Programming Hub	Programming	*"Coding and programming app to learn to code with HTML, Javascript, C, C++, C#, Swift, Python, R, Java, CSS, etc."*	14,307
Chordify	Music	*"To learn guitar, ukulele, and piano chords. Chordify gives you the music chords for any song and aligns them to the music."*	2,702

Table 1. Description of the collected data

2.2 Data Analysis

Researchers have used computationally intensive theory development to identify parsimonious, intelligible, and communicable sets of construct linkages (Berente et al., 2019). As a content analysis methodology, machine learning and natural language processing of textual data are gaining popularity in information systems research and related domains. Scholars utilize clustering techniques to find categories and linkages, which involves a process of convergence to synchronic relationships (Hastie et al., 2009). Big textual data has been developed by machine learning techniques, the expansion of social media platforms, and the availability of rich text records from various sources. Topic modeling is an unsupervised machine learning technique for textual data that discovers an overview of themes discussed in documents (Eickhoff & Neuss, 2017) by using a Machine Learning algorithm such as LDA. We can use different algorithms to conduct topic modeling in our research. Blei et al. (2003) presented the Latent Dirichlet allocation (LDA) to discover textual data topics. LDA is a "statistical model of language" used by a Bayesian probabilistic model to uncover latent structures. It views documents as random mixtures of latent structures and clusters, where each cluster or topic is a distribution among words (Blei et al., 2003). LDA assumes that that "each word in a document [is modeled] as a sample from a mixture model, where the mixture components are multinomial random variables that can be viewed as representations of 'topics.'" The result of LDA will be a matrix of topics and their top keywords. It also generates the probability of a document belonging to each topic. In other words, the words in a document determine what the topic of that document is.

3 Findings

In this section, we present the findings of our study. First, we present the way users express their different motives for using the app. We will study these motives across four different applications and present the common pattern of writing a review among users across different apps. The relationship of the level of each motive to the user satisfaction of reviews will be tested, and the results will be presented in terms of Standardized Coefficients Beta. The generated model will be tested in four equivalent apps in the market to test the robustness of the findings.

3.1 Perceived Usefulness

The Perceived Usefulness construct in our study refers to the practicality of the learning apps for users. Users have expressed different perspectives of the usefulness of learning apps. Table 2 shows the representative keywords for the PU construct in each application. Using terms like 'helpful' or 'useful' is shared among users when they express the practicality of an app. They also find such apps useful for their current education in school, college, or private classes. In these kinds of reviews, learning apps have been compared to traditional ways of teaching since users find it as an alternative choice for different reasons. These reasons include providing a variety of learning content, an effective way to practice daily to master something, clear and easy to follow explanation, keeping uses sharp, smart, and up to date, and a suitable choice for beginners. We also have found minor reasons among users, such as a productive way of using their smartphone while staying at home for lockdown, for instance.

Mobile App	Representative keywords
Duolingo	Class, School, Teach, Study, Explain, Explanation, Understand, Know, Skill, Memorize, Practice, Repetition, Speak, Write, Read
Elevate	Helpful, Help, Useful, School, Teach, Train, Exercise, Improve, Improvement, know, Skill, Active, Mind, Sharp, Smart
SoloLearn	Helpful, Help, Useful, Study, Practice, Beginner, Skill, Concept, Improve, Know, Knowledge
Yousician	Help, Useful, School, Teach, Beginner, Start, Step, Improve, Practice

Table 2. Representative words for Perceived Usefulness from emergent topics

3.2 Perceived Enjoyment

The Perceived Enjoyment construct in our study refers to the engaging, fun, and entertaining learning experience provided by the learning apps using different techniques, including game-based learning, gamification, playful design, etc. Table 3 provides our final list of representative keywords for the PE construct for each app. Users across all apps share their hedonic experience by using terms including 'fun,' 'enjoy,' 'experience.' Different aspects of hedonic learning experience being expressed by users in the form of online reviews could be the friendly and interactive design of the app that makes the learning experience fun, addictive, simple, and interesting. We can also see reviews focusing on how such learning apps provide novelty in the learning experience by offering new and different ways of learning.

Mobile App	Representative keywords
Duolingo	Fun, Enjoyable, Interactive, Friendly, Easy, Addictive
Elevate	Fun, Enjoy, Engage, Interesting, Experience, Addictive, Play, Game, Challenging, Easy, Design, Graphic, Interface
SoloLearn	Fun, Experience, Cool, Interest, Interesting, Easy, Simple, Friendly
Yousician	Fun, Enjoy, Experience, Cool, Easy, Simple

Table 3. Representative words for Perceived Enjoyment from emergent topics

3.3 Perceived Cost

The next construct in our study is Perceived Cost. This construct refers to how users perceive the cost of an app and whether they find it affordable or worth paying money for. Table 4 shows the most indicative words in online reviews related to the cost of using an application. As we can see, users show almost the same pattern of behavior in writing such reviews. Users of each app use the same language to express such reviews and show less variety than other constructs of this study. Users tend to complain about an application becoming pricy or subscription-based in a new version. Some users think such a price might not be worthy for such apps and others see the free or trial version as very limited compared to the premium or plus version.

Mobile App	Representative keywords
Duolingo	Free, Subscribe, Subscription, Pay, Buy, Purchase, Price, Money, Plus, Trial, Premium
Elevate	Free, Subscribe, Subscription, Fee, Pay, Payment, Buy, Money, Expensive, Premium
SoloLearn	Free, Subscribe, Subscription, Fee, Pay, Buy, Money
Yousician	Free, Subscribe, Subscription, Pay, Buy, Price, Money, Expensive, Trial, Premium

Table 4. Representative words for Perceived Cost from emergent topics

3.4 Guided Topics

The output of the last step is the most representative keywords for each construct for each app separately. We intentionally keep them separated since the difference in the meaning of some words in different contexts. For example, the word 'play' means playing a game in the Elevate app, but that word means playing an instrument in the Yousician app. In addition, users have different motivations for using a learning app, given their objectives. For example, some users use such apps to do their homework, but others may merely use them to broaden their knowledge in one subject.

We used those representative keywords as the seed words of three universal clusters of reviews for each construct. We also had to create the fourth cluster for the irrelevant reviews. The result of this analysis is a variable for each construct showing the relevance of a review to each dimension. This variable could be from 0 to 100, showing the loading of each universal topic for the reviews. Each review will have a loading value for all constructs in our study: PU, PE, and PA. We also have included the metadata of the reviews in the analysis as the control variable so that we make sure the variability in the dependent variable is not caused by those variables: The length of a review and the version of the app.

3.5 Regression analysis

The next step is to run Multiple Regression to investigate the coefficients of IVs in our model. We divided our model into two steps to test the control variables: base (only control variables) and main (all variables) models. The dependent variable in our model is User Satisfaction that is measured by the star rating of the reviews. Table 5 shows the standard coefficients of the variables for each app. We consider the corpus of the reviews from each app as a separated data panel and run the analysis separately. The results show that the Perceived Usefulness and Perceived Enjoyment show a significant positive association with the User Satisfaction while the Perceived Affordability negatively impacts User Satisfaction. The pattern is the same across all data panels, showing the relationship's robustness given the difference in users' objectives and the learning content. Besides, the length of the reviews seems to be negatively correlated with the user ratings showing that dissatisfied users tend to write lengthier reviews than those expressing their satisfaction with the app. Regarding the positive influence of each variable, the practicality of a learning app seems to have a higher degree of importance from users' perspective than the hedonic experience.

	Duolingo (Second language)		Elevate (Brain Training)		SoloLearn (Programming)		Yousician (Music)	
Construct	Base	Main	Base	Main	Base	Main	Base	Main
Version	.006	.016 *	.051 *	.042 *	-.086 *	-.067 *	.073 *	.070 *
Length	-.181 *	-.234 *	-.174 *	-.168 *	-.174 *	-.165 *	-.221 *	-.269 *
Usefulness		.145 *		.242 *		.133 *		.240 *
Enjoyment		.217 *		.176 *		.109 *		.195 *
Cost		-.137 *		-.309 *		-.192 *		-.102 *

Significance: <.05 *
DV: User Satisfaction (1 to 5 rating)

Table 5. Standard Coefficients Beta (β) of the variables explaining user satisfaction (Rating)

3.6 Robustness Test

To check the robustness of the results of the last step in our study, we aimed to collect the data from 4 equivalent apps to the main ones to see if we could see the same pattern of associations among variables. We chose four different apps through which users learn a second language, play brain training games, learn how to code, and learn to play an instrument. These four apps could be the potential competitor of the main apps in our study in the market. Given the similarity of the apps and the shared goal of users for using them, we argue that the demographic of the users and their motives share the same pattern. To test these new data panels, we used the exact representative keywords from the main apps to generate the universal clusters in these new apps. Table 6 shows the result of the robustness test, and we can see the direction of the relationship among IVs and the DV is the same as the main apps. However, there might be a noticeable difference in terms of the importance of each variable and the influence on User Satisfaction.

	Babble (Second language)		Peak (Brain training)		Programming Hub (Programming)		Chordify (Music)	
Construct	Base	Main	Base	Main	Base	Main	Base	Main
Version	-.088 *	-.059 *	.160 *	.138 *	.017	.015	.073 *	.083 *
Length	-.118 *	-.067 *	-.207 *	-.226 *	-.170 *	-.116 *	-.101 *	-.071 *
Usefulness		.096 *		.317 *		.078 *		.187 *
Enjoyment		.198 *		.105 *		.110 *		.130 *
Cost		-.329 *		-.204 *		-.216 *		-.269 *

Significance: <.05 *
DV: User Satisfaction (1 to 5 rating)

Table 6. Robustness test of the relations between variables in the model

4 Discussion

In this section, we address the proposed research questions of this study. First, we show how this study's findings help us discover the pattern of users expressing their utilitarian, hedonic, and monetary motivations in online reviews. We then analyze the relationship of each motivation to user satisfaction and will discuss whether this relationship stays the same given the difference in app type and learning content.

Most users find learning apps useful for their classes and courses in school and college regarding utilitarian motivation. They mostly use them to pass their exam, get a better grade, or do their homework. The findings suggest that users find learning apps suitable for beginners in a topic and want to start from scratch. This might be since trying such an app has less cost and effort, and they can withdraw at any time if they don't find it helpful. In addition, people have their mobile devices most of the time, and this gives them more opportunity to practice in their spare time or when they are in lockdown and have less access to traditional ways of learning. This motivation is the most diversely expressed one in our model as it is directly associated with users' goals in using an application. For example, users who use a brain training app might have completely different objectives than those who use a learning app to learn how to code.

We found that users tend to show similar behavior in writing a review about the fun learning experience regarding hedonic motivation. This motivation has less diversity in the familiar words and pattern of behavior than the utilitarian motivation. Our findings suggest that people seek learning apps as an alternative to other learning methods due to the engaging experience these apps can offer. Users think having a fun learning experience allows them to stay active and show consistent progress leading them to get better learning outcomes. They think such a learning experience is interactive, engaging, addictive, and very novel. We argue that the learning app could offer such a learning experience through utilizing gamification, playful design, and simplicity in the user experience design.

The monetary motivation of using learning apps is least diversely expressed in the model as all users, regardless of the learning app, show similar behavior when reviewing the cost of using an app. All the reviews related to the affordability of a learning app focus on the difference between a free version and a premium version that needs a monthly or yearly subscription. They show dissatisfaction if they think the free version of a learning app is minimal compared to the premium version. We argue that designers of such apps might be mindful of users' behavior and set the free version's limitation following users' needs and expectations.

In terms of the relationship of each user's motivations to user satisfaction, we observed that Perceived Usefulness and Perceived Enjoyment have a significant positive relationship with User Satisfaction. The results reveal that the Perceived Cost construct has a negative association with User Satisfaction. We tested these relationships across apps with different learning types. The direction of each relationship is the same, given the type of the app. We also test the robustness of the results by testing the model for a new set of learning apps. These new sets of apps are the equivalent of the main apps of this study, and we might assume them as potential competitors as well. Our findings suggest that users show the same behavior in the equivalent apps as well. Figure 2 present a summary of all the different motivations users have shown in the reviews.

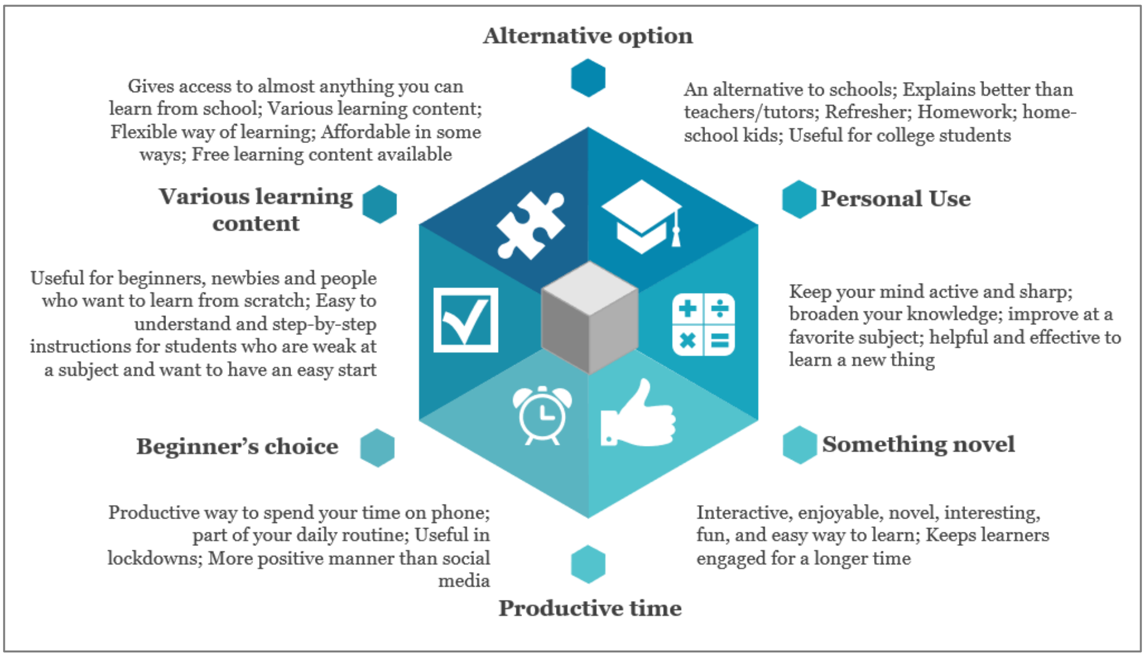

Figure 2. The summary of motivations for using mobile learning apps

5 Conclusion

We argue that our study will make both academic and industrial contributions: From a business standpoint, our method may be used to extract insights from online reviews written by real users of the learning apps in a semi-automated manner. We believe that users' needs may evolve over time for a variety of reasons. As a result, businesses interested in using gamification should be aware of the changing nature of consumer needs and goals to maintain their competitive position while prioritizing dynamic user needs. From an academic perspective, our study proves the importance of online reviews in understanding utilitarian, hedonic, and monetary motivations among users. This research shows how advanced text analytics may add value to the literature and offers an alternative way to measure the level of Perceived Usefulness, Perceived Enjoyment, and Perceived Cost from text data provided by users in the form of online reviews.

Our study is primarily constrained by the limits of text data collected as online reviews by consumers or users. First, several biases govern consumer responses when providing online reviews, such as self-selection and response biases (Hu et al., 2009; Li & Hitt, 2008), and text mining techniques can only estimate the subjective opinion of users or customers (Feldman, 2013). Second, the linguistic content typically entails noise due to its inaccuracy (Loughran & McDonald, 2016). Third, we only focused on the reviews written in English and omitted the other languages. However, reviews written in a language other than English were not significant. Despite the contributions of industry and academia, more work remains to be done. Future research will focus on application studies in other fields and attempt to capture other type of construct from online reviews. Other text data sources, such as Twitter, Facebook, and Reddit, could also provide further insights into user interaction with mobile learning apps.

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Appendix 1. Collinearity diagnosis

Before testing our model, we need to make sure to diagnose the collinearity problem among our IVs. We use the Tolerance and Variance Inflation Factor metrics to assess the collinearity of our variables. They are based on the R-squared value obtained by regressing a predictor on all other predictors in the analysis. More VIF shows the presence of multicollinearity. The inverse of VIF is called Tolerance, so the VIF and TOI have a direct connection. We set the cut-off for the Tolerance to be 0.2 and for the VIF to be 5. Table 7 shows the results of the collinearity diagnosis. All the variables in different data panels have a VIF value lower than five and Tolerance higher than 0.2. This result means we don't have the multicollinearity issue in our model.

	Duolingo		Elevate		SoloLearn		Yousician	
Construct	Tolerance	VIF[1]	Tolerance	VIF	Tolerance	VIF	Tolerance	VIF
Version	.998	1.002	.999	1.001	.992	1.008	.999	1.001
Length	.609	1.642	.640	1.563	.847	1.181	.761	1.314
Usefulness	.712	1.405	.868	1.152	.944	1.060	.917	1.090
Enjoyment	.982	1.018	.874	1.144	.976	1.025	.979	1.022
Cost	.836	1.196	.761	1.314	.905	1.105	.829	1.206
Cut-off	<0.2	>5						

Table 7. Collinearity statistics

[1] . Variance inflation factor