How Pricing and Ratings Affect Perceived Value of Digital Detox Apps

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ABSTRACT

As the number of mobile apps has exploded over the last decade, different pricing models have emerged (e.g., free, paid, freemium). However, it is not clear how these models affect users' perceptions of the value of apps that promote behavior change, such as digital detox apps, and what role social ratings play in this relationship. This paper investigates this issue using an experimental approach. The results of a controlled between-subjects experiment (N = 894) suggest that pricing models significantly influence the perceived value of digital detox apps. Digital detox apps using the paid model are perceived to be significantly less valuable than free and freemium apps. No significant difference has been found between free and freemium pricing models. Theoretical and practical implications are discussed.

KEYWORDS

Pricing, Ratings, Digital Detox Apps, iOS, Apple App Store, Digital nudging, Free, Freemium, Paid, In-app purchase

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1 INTRODUCTION

In a typical offline scenario, consumers perceive price as an indicator of quality, [35] which is in line with the conventional saying "You get what you pay for". The relationship between price and quality is strong enough to influence the assessment of a product's quality [47]. The price prompts an individual to think about the product's value [24] and the chances of incorrect assessment increases with the increasing price levels [47]. Price acts as a heuristic cue and is more readily discernible than the quality of the product [59].

With the emergence of the digital age, researchers have discovered that the online behavior of the consumer differs from their offline behavior [10]. The growth of e-commerce has substantially benefited consumers by giving them a price advantage [46]. In e-commerce, customers have a tendency to compare the price offered by the current vendor with the price offered by other vendors and then form their price-value perceptions [25]. Another important factor that influences how consumers infer product quality online are ratings [14]. Consumers rely heavily on average ratings to form quality inferences [9], even when research suggests that online ratings are systematically biased and easily manipulated [2], and do not accurately reflect true product quality [26]. Even though there has been extensive research on price and ratings biases for products *offline*, it is still unclear how these factors affect perceived value for *digital* products.

One particular type of digital product that emerged over the last decade is digital detox apps, sold on so-called app markets. "Digital detox" refers to periodic abstinence from social media [45], and apps that aid in this process are known as digital detox applications. In one of those markets, the Apple App Store, there are currently over two million apps available [40] and a growing number of digital detox apps in the category of productivity and health. On these markets, an app's pricing is a critical issue and prices are expected to differ significantly across different categories of apps [48]. Pricing in app stores generally falls into one of three categories: (1) free, (2) paid, or (3) freemium (in-app purchase i.e, where a basic version of the app is given away for free and consumers can purchase premium features from within the app later on). However, not much is known about the influence of these pricing models on value perception. For instance, it was recently reported by Gray et al. [19] that consumers may perceive the digital product in a negative light and feel manipulated if a payment is required for the digital product or in-app purchases are allowed.

Thus, we aim to tackle the following research question: *How do pricing models impact how consumers perceive the value of behavior-change apps?*

To address this question, this paper is structured as follows. Section 2 discusses the theoretical background and hypotheses. Then, Sections 3 and 4 detail the experimental design and the results, respectively. Finally, while Section 5 discusses theoretical and practical implications, Section 6 wraps up with a conclusion.

2 THEORETICAL BACKGROUND & HYPOTHESES

In this section, we introduce and describe the theoretical background around perceived value and known biases related to pricing as well as social ratings. This background leads to the formulation of seven research hypotheses.

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2.1 Perceived value

Perceived value is a principal construct to attain better insight of consumer behavior in mobile information systems [50] and e-services [33]. Perceived value is defined as "global evaluation of the consumer regarding the utility of the product that hinges on the perception of what is received in exchange for what is given" [61]. There is much empirical evidence that perceived value influences the perception and usage behavior of digital artifacts [7, 20, 43]. Consumer's perception of value is important as it creates attitude of consumption [46]. Perceived value is shown to be positively associated with product attitude [60] and is an important factor in promoting the usage of the app [5, 36, 56].

2.2 Pricing models

Extensive studies on consumer behavior have shown that buyers perceive positive price-quality relationship [23, 39, 54]. In the context of offline price evaluation, human minds assume higher price means better quality [32]. For instance, Lee et al. [32] showed how adding a price changed the perception of value. They asked students to obtain photo-editing software to complete an assignment due in a week or three months' time. Students were asked to choose between software that was either feature-rich and complicated (Photoshop) or simpler and quicker to get started (e.g. iPhoto). While some were told that the software would be provided free of charge, others were told that they would need to pay. Curiously, students opted predominantly for the 'convenient' choice when the items were free. Strikingly, they preferred the complex software when the price was added, even when the due date was only a week away.

Furthermore, relative high or low price can affect the experiential value of a product, including its efficacy [24]. When products are discounted, people feel that the product's functionality is also reduced [53]. With free options, users with strong inferential beliefs about the link between price and quality can associate inferior quality with low value [41].

As indicated in the Introduction, in the context of mobile application stores such as Apple's App Store, the pricing model can be of three types: free, paid, and freemium (i.e., basic functionalities are free, while extensions, called premium functions, can be purchased from within the app). The freemium model allows the consumer to purchase a variety of content, including subscriptions, new features, and services within the app [58]. It is usually offered to users by indicating that the app is free, but offers the possibility of *In-App purchases*. The worldwide web has engendered an attention to cost transparency [55]; similar apps are available with different pricing models (free, paid, and freemium) with lower search costs and, hence, more efficient buyer search [42]. For instance, nearly 40% of the sellers were observed offering more than ten apps, while about 60% offer apps in more than one category [30]. This ignites rapid "app competition" subsequently, making sellers release apps on free/freemium model on Apple's App store [3]. Consistent with previous literature indicating that pricing factors affect perceived value [11, 41], we make the following hypothesis:

H1: Pricing models (free, paid, freemium) on app store significantly influence the perceived value of digital detox apps

However, research on the price-quality relationship in this context is not yet mature and results offer contrasting findings. For instance, recent research has shown zero-price effect for digital products, i.e., a price tag of "free" increases the demand for the free product [22, 41]. Assuming that a free app may evoke positive reactions, it is also possible that the same aspect could spark an opposite reaction in the app store. However, this assumption still requires further scrutiny. Indeed, users might hold the belief that a lower price is indicative of inferior quality, triggering a price–value schema or product performance risk [12]. Researchers have also discovered that providing competitive rates or discounts increases consumers' perceived value [35] and app downloads [3]. Thus leading to the following hypothesis:

H1a: The value of a digital detox app with a *paid* pricing model will be perceived as being lower than the value of an app using a *free* pricing model

The freemium pricing model is fairly recent and it is not yet clear how it affects the perceived quality and how it compares with standard paid and free models. Nevertheless, research has shown that its introduction was linked to an increase in app demand [17], thereby positively influencing the app revenue performance in Apple's App Store [49]. With its current design on the app market closely resembling the free pricing model, we hypothesize that this model is a middle option between paid and free. More formally, we make the following hypotheses:

H1b: The value of a digital detox app with a *free* pricing model will be perceived as being higher than the value of an app using a *freemium* pricing model

H1c: The value of a digital detox app with a *freemium* pricing model will be perceived as higher than the value of an app using a *paid* pricing model.

2.3 Online rating bias

In the digital environment, social ratings have become ubiquitous to assess the quality of any product and service. Users can provide ratings through various mechanisms depending on the platforms, such as only positive (e.g., Instagram, Facebook, Twitter with a simple heart, or a like), positive and negative (e.g., Youtube with a thumbs-up and a thumbs-down), a scale from positive to negative rating (e.g., uber, app store, amazon with ratings from 1 to 5 stars).

User ratings are subsequently aggregated to provide an overview of the evaluation (e.g., total number of hearts, percentage of likes or dislikes, average number of stars). As such, ratings are heuristics that facilitate decision making [18] by simplifying a large quantity of information [15]. Hence, ratings become influential when choosing a product [6]. These aggregated ratings represent a form of social influence, which involves accepting information or advice from an unknown person [8, 15]. Ratings have become relevant when making quality inferences [27] and taking purchasing decisions [31, 62].

In consideration of digital goods i.e., mobile apps on an app store, the star ratings is a vital aspect to infer quality of the app [21]. On the Blackberry app store, researchers found highly rated apps were downloaded more frequently [13]. Most often, users rate the apps after they have begun using the app regularly, hence, app ratings could assist as a proxy for assessing an app's value [38, 57]. The quality of the app is uncertain before purchase/download and ratings have shown to assist in settling quality uncertainty [28, 34]. Hence, we make the following hypotheses:

H2: Ratings (Low, High) of a digital detox app will significantly influence the perceived value of the app.

H2a: The value of a digital detox app with a *high rating* will be perceived as higher than the value of an app that has *low ratings*

In the presence of ratings as a cue in the digital environment accompanied by pricing models (free, paid, and freemium), we hypothesize that ratings and price may interact to raise the value of an app.

H3: Pricing models and ratings will jointly interact to elicit a higher perceived value of a digital detox apps.

3 EXPERIMENTAL DESIGN

We ran a 3 (free, paid, freemium) x 2 (low rating, high rating) between-subjects experiment (N = 894) where participants were exposed to a made-up app description on a mock Apple App store and asked about the value they perceived.

As depicted in Figure 2, the app description used was that of a digital detox app, i.e., an app that helps users reduce their consumption of social media [44]. Such apps have recently gained momentum and are in the general area of health apps. In the Apple App store, there is no price shown for free apps. Instead, there is a button that says *"GET"*. For the freemium pricing model, the same *"GET"* button is used, and an *in-app purchases* text is added next to it. We used these designs in our experiment. In app stores, the average price for paid apps range from $ 0.99 to $ 15.99 [52]. For the paid pricing model in the experiment, we priced the app at USD 10, as shown in the figure. For ratings, we used stars, as is customary in the app store. Ratings range from one to five stars, with a median at 4 stars [1]. For the low rating condition, we used an average score of 1.5, and for the high rating condition, we used an average of 4.2.

The participants were recruited from a digital platform called Prolific. Participants were filtered based on their smartphone, location and their social media use. Only the participants who are native English speakers who use social media for at least one hour a day and use an iPhone were considered. From Prolific, the online participants were directed to an anonymous Qualtrics link. The online participants were made aware that the research concerns an evaluation of a digital detox app.

Pricing model	Rating: Low	Rating: High
Free	147	150
Paid	151	147
Freemium	149	150
Total = 894		

Figure 1: Number of participants in each condition

Participants were randomly assigned to one condition. A pilot experiment (n = 200) consisting of a US pool of participants suggested that the experiment took a maximum of five minutes to complete. Based on those results, the participants were compensated USD 1 for their participation. The online participants first had to read the instructions and agree to the conditions of the study. After this, each participant was confronted with a randomly assigned app description (see Figure 2). As hinted above, app descriptions in all groups were identical except for (1) the text in the download button (GET for the free condition, USD 10 for the paid condition, and GET with the In-App Purchases mention for the freemium condition, and (2) the number of stars (1.5 in the low ratings condition and 4.2 in the high ratings condition). Apart from these app descriptions, everything else in each experimental group was identical. Immediately after the participants clicked past the app description, their attitude towards the app as well as their perceived value was measured. Thereafter, they received attention checks (i.e, What was the price of the app? What was the rating of the app?).

4 RESULTS

The measures adopted in the study are validated scales in the literature (seven-point Likert-scale). To measure different aspects of perceived value the scales from Mathmann et al. [37] were adopted. Cronbach's alpha value for perceived value construct used in this study was .889. According to George et al. [16] values >.8 are considered good. The measure was robust in terms of its internal consistency reliability. The manipulation check by the Chi Square Test of Independence confirmed that participants appropriately interpreted the treatments of price $\chi^2(10, N = 894) = 859.95$, $p < 0.001$ and ratings $\chi^2(5, N = 894) = 527.99$, $p < 0.001$.

To examine our hypothesis H1, H2 and H3, we used a two-way ANOVA. The precondition to conduct an ANOVA was met, i.e., the Levene's test for homogeneity of variances across treatments failed to reject the equal variance dispersion hypothesis (F value of 1.602, $p = 0.157$). Table 1 shows the results for the main effects (pricing model and rating) and their interaction effect (pricing model x rating). We found a significant main effect of pricing models ($F = 5.813$, $p < 0.001$) as well as of ratings ($F = 68.138$, $p < 0.001$). The results indicate that there is a difference in perceived value by types of pricing models and rating respectively. H1 and H2 are supported. However, the interaction effect between pricing models and rating did not reach statistical significance ($F = 0.309$, $p > 0.05$) (see Figure 3). Thus, H3 is rejected.

Table 1: Results of Two-way ANOVA

Dependent Variable: Perceived value	Df	F value
Pricing models (H1)	2	5.813^{***}
Rating (H2)	1	68.138^{***}
Pricing models:Rating (H3)	2	0.309

Note: *p<0.1; **p<0.05; ***p<0.01

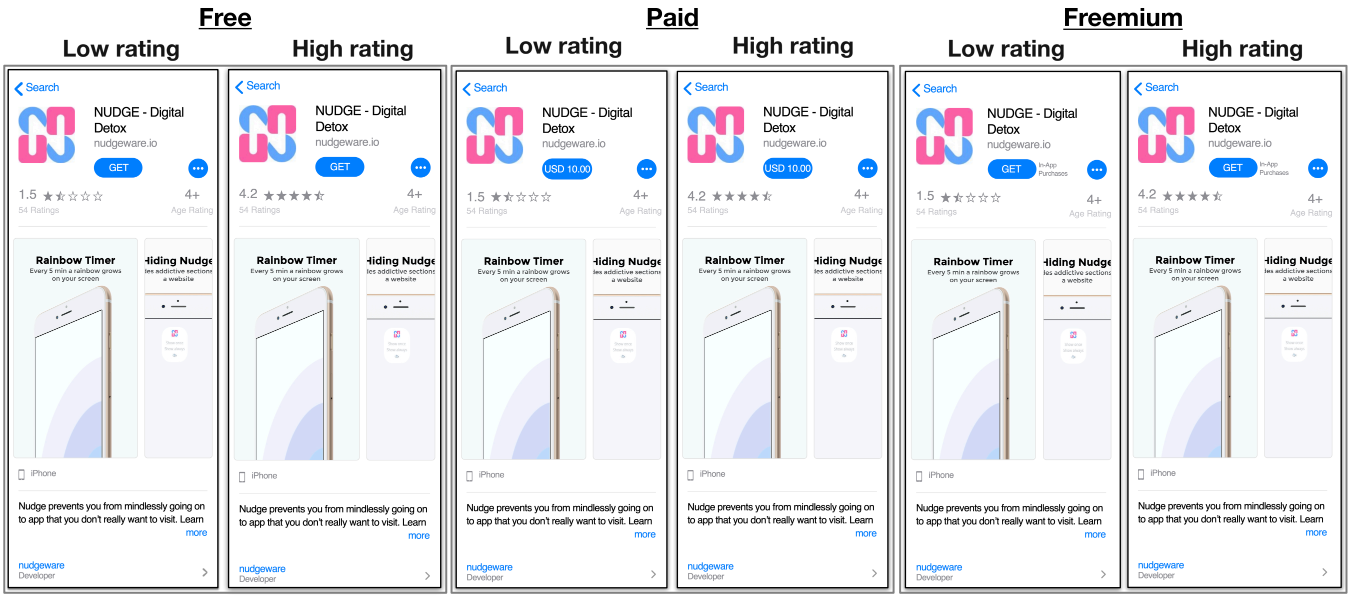

Figure 2: Treatments

To test hypotheses H1a, H1b, H1c and H2a, we conducted simple comparisons t-tests. The mean difference estimates on perceived value (DV) between each contrast of pricing models and rating with their standard errors (in parentheses) and p-values are shown in Table 2. The results show that the perceived value is significantly higher for the free compared to the paid pricing model ($\beta = -0.360$, $p < 0.01$), allowing us to support H1a. There is no significant difference in perceived value for freemium compared to the free model ($\beta = -0.130$, $p > 0.05$). Thus, H1b is rejected. However, perceived value is significantly higher for freemium compared to the paid pricing model ($\beta = 0.230$, $p < 0.05$), supporting the hypothesis H1c. In the case of ratings, perceived value is significantly higher for high rating compared to low ratings ($\beta = 0.742$, $p < 0.01$). H2a is supported.

Table 2: Simple Contrasts of Price and Ratings

Dependent Variable: Perceived value (PV)		
	Estimate	p
Paid vs Free (H1a)	-0.360 (0.110)	0.001
Freemium vs Free (H1b)	-0.130 (0.110)	0.236
Freemium vs Paid (H1c)	0.230 (0.113)	0.036
High rating vs Low rating (H2a)	0.739 (0.089)	0.000

Note: Std. Errors in parentheses

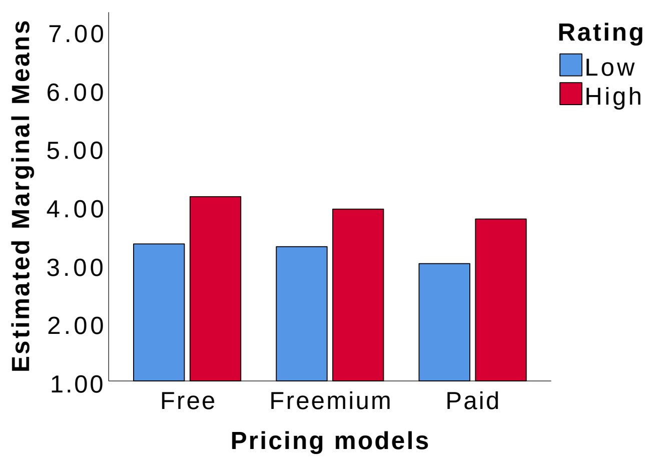

Figure 3: Impact of pricing models x ratings on perceived value

5 DISCUSSION

In this research, we investigate an essential heuristic when assessing an app: pricing. We sought to answer the question: How do pricing models impact how consumers perceive the value of mobile apps? We have included another key heuristic in our research, namely ratings. We assumed free and freemium pricing models to be positive influencers on the perceived value of the app in comparison with paid pricing model. We found support for the fact that putting a price on a mobile app makes it less valuable for customers. Furthermore, we found no significant difference between the free

Table 3: Hypothesis results

H1: Pricing models (free, paid, freemium) on app store significantly influence the perceived value of digital detox apps	**Supported**
H1a: The value of a digital detox app with a *paid* pricing model will be perceived as being lower than the value of an app using a *free* pricing model.	**Supported**
H1b: The value of a digital detox app with a *free* pricing model will be perceived as being higher than the value of an app using a *freemium* pricing model	Rejected
H1c: The value of a digital detox app with a *freemium* pricing model will be perceived as higher than the value of an app using a *paid* pricing model	**Supported**
H2: Ratings (Low, High) of a digital detox app will significantly influence the perceived value of the app	**Supported**
H2a: The value of a digital detox app with a *high rating* will be perceived as higher than the value of an app that has *low ratings*	**Supported**
H3: Pricing models and ratings will jointly interact to elicit a higher perceived value of a digital detox apps	Rejected

and freemium models in terms of perceived value. Finally, we confirmed that high ratings influence the value of an app positively. However, we did not find an interaction between price and ratings.

5.1 Implications for research

From a theoretical perspective, we have responded to the call for researchers to focus on the relationship between price and ratings that are yet to be discovered on app stores [13]. We added new insights about the relationship between price and ratings and its influence on perceived value for mobile apps, while previous research has dealt with strategies to increase sales performance in the app store market [29], investigated the effects of price on online consumer reviews [34], inspected consumers' willingness to pay for top-ranked apps in the app stores [4], examined correlations between customer rating and popularity (rank of app downloads) [13] and probed rating valence sensitivity in app stores contingent on economic factors [28]. To the best of our knowledge, we are the first to have examined both factors (pricing models and rating) and their interactions concerning behavior-change apps. We have added value to online decision-making research in two ways. 1) Showing a zero price (free) has a positive influence on perceived value, unlike the paid app that negatively influences perceived value. At the same time, freemium enjoys the luxury of positively impacting perceived value compared to the paid app and remaining neutral in comparison with the free apps. Previously, the zero price effect has been noticed for hedonic products [41, 51]. Conversely, this research shows the zero price effect (free) to be true for even utilitarian products (health apps). 2) Ratings positively influence the perceived value of the behavior-change app in the app store.

5.2 Implications for practice

From a practical perspective, we want practitioners to take note of three major points. First, individuals experience a zero-price effect on the app stores meaning users perceive higher value with free apps. Second, freemium is a suitable business model as compared to a paid app, as the requirement to pay negatively influence the perceived value of an app. Finally, it should be noted that ratings also exert an influence on perceived value, which indicates that a change in pricing model might not be enough to counter a negative change in ratings.

5.3 Limitation

This paper is not without limitations. As the experimental design space is finite, we had to focus the scope of investigation to a specific area. Specifically, we focused on a particular class of applications, i.e., digital detox apps, and we placed particular limits on price (USD 10) and rating (1.5 and 4.2 stars) cues. Future research should further explore the design space to understand how value perception changes for other price and rating values and to ascertain if there is a point when a change in pricing model can trump a change in ratings. Furthermore, future work should also investigate other classes of apps to understand how much of our findings can be generalized across application types and how much is specific to digital detox apps.

6 CONCLUSION

With over two million apps available in mobile app stores, it is crucial to understand how users perceive their value. This paper aimed at tackling this issue by zooming in on pricing models (free, paid, freemium) and ratings (low, high) as value predictors. Our controlled experiment (N = 894) indicates that there is a significant effect of pricing model and of ratings towards perceived value, but no interaction between these factors was found. In more details, the findings suggest that the value of paid apps is perceived as being significantly lower than free apps and apps using the freemium pricing model. No difference was found between these latter two pricing models. Thus, a freeemium model could enjoy the perceived value of a free app when it comes to choosing the product online, while potentially bringing in revenues later, through in app purchases.

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