# What drives add-on sales in mobile games? The role of inter-price relationship and product popularity

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**Abstract**

Mobile app developers monetize in-app purchases or add-ons whose prices can be compared with the prices of the app and other add-ons. However, little attention is paid to pricing methods of the base and add-on products to maximize add-on sales. This study examines how absolute and relative prices of new add-ons—compared with those of the base and existing add-on products in the same product—influence their sales with a consideration of product popularity. Using a sample of 7,108 weekly observations derived from 74 mobile games and 514 add-ons, we find that the absolute (relative) price of a new add-on has a positive (negative) effect on the add-on sales. Moreover, we find that the negative relationship between relative price and sales is attenuated by base sales and review volume. This study provides app developers a substantial guideline for optimally pricing base and add-on products under different levels of product popularity.

*Keywords:* Mobile application; Add-on pricing; Relative price; Product popularity

## 1. Introduction

The practice of pricing add-on products for an existing base product has become increasingly prevalent in information goods such as video games (Healey & Moe, 2015), digital contents (Yu, Hu, & Fan, 2011), and mobile apps (Guo & Papatla, 2015). In a platform-mediated market, consumers first purchase a base product and then purchase add-on products for that base product during the product life cycle. Firms typically rely on the base and add-on pricing model to increase product sales in extremely competitive products like mobile apps (Guo and Papatla, 2015). In the mobile app market, gaming (79%) and non-gaming app (50%) developers consider in-app purchases (i.e., add-on products) as the most common monetization strategy (Miller, 2017).

Although app developers can launch new add-on products subsequently through software upgrades, research has mainly dealt with the simultaneous pricing of multiple products such as bundling (Stremersch & Tellis, 2002; Venkatesh & Mahajan, 1993) and tying (Whinston, 1990). However, base and add-on products are different from bundled or tied products because consumers' add-on purchase decisions require prior purchase of the base product, and add-on prices can be unobserved whereas bundled prices are all revealed (Shulman & Geng, 2019). Research on add-on pricing has also focused on the conceptual dimension of the base and add-on pricing (Ellison, 2005) and examined the inter-relationship either between base and add-on products (Yu et al., 2011) or among multiple add-on products (Wu, Chen, & Cho, 2013). In addition to price itself, other consumers' actual purchase actions and/or opinions, which indicates the level of product popularity (Choi, Ko, Medlin, & Chen, 2018), may affect consumers' purchase decisions on add-on products (Healey & Moe, 2015). Few studies have considered the independent and interactive effects of add-on price and non-price (e.g., product popularity) factors in a single framework.

To fill these gaps, we attempt to empirically investigate strategic ways of setting optimal prices for add-on products of mobile games in terms of maximizing their sales. Specifically, we study (1) how absolute and relative prices of add-on products, compared with the prices of previously launched base and add-on products, influence their sales and (2) how relative prices perform differently under heterogeneous product popularity. We base our investigation on a conceptual framework in which price plays both an informative role—consumers make absolute judgments about the add-on price itself (i.e., absolute price)—and an allocative role—consumers make comparative judgments about the add-on price with other price information (i.e., relative price) (Rao, 1984; Völckner, 2008). Regarding product popularity, we consider two popularity cues, namely, action-based and opinion-based, that affect consumers' purchase decisions (Chen, 2008; Chen, Wang, & Xie, 2011; Cheung, Xiao, & Liu, 2014). Using a sample of 7,108 weekly observations derived from 74 mobile games with a non-zero base price and 514 in-app purchases, we obtain the following findings: (1) the absolute price has a positive effect on add-on sales; (2) the relative price has a negative effect on sales; and (3) the negative relationship between relative price and sales is attenuated by product popularity.

Our study extends to the extant literature in several important ways. First, this study adopts the dual roles of price, namely, informative and allocative, to investigate how absolute and relative price information of add-on products influence their sales in the hedonic product market. Second, this study investigates the moderating role of two popularity cues for mobile games (action-based and opinion-based), which have received limited attention in the literature (Chen et al., 2011; Cheung et al., 2014). Third, this study is one of the first attempts to investigate the effect of the inter-price relationship among base and add-on products on the add-on sales in the context of mobile games. Although Guo and Papatla (2015) examined the importance of inter-relationship between base and add-on prices in mobile apps, they measured the volume and valence of ratings (i.e., a proxy for base product sales) as market outcomes, not the actual sales of add-on products. Finally, this study provides practical implications for mobile game developers who should take actionable steps in pricing base and add-on products, which can be launched sequentially, for add-on sales maximization.

The structure of the paper is as follows. First, we review the extant studies on add-on pricing and build a conceptual framework and hypotheses regarding how absolute and relative add-on prices and product popularity influence the sales of add-on products independently and interactively. Next, a log-linear regression model is applied to an actual transaction dataset obtained from a leading mobile app market in Asia. Following these analyses, a discussion of their theoretical and practical implications is made.

## 2. Literature review

### *2.1. Dual roles of add-on price*

Pricing strategies for multiple products can be identified by two key dimensions: the inter-product relationship (e.g., level of contingency) and the launch timing (e.g., simultaneous or sequential). The inter-product relationship consists of (1) non-contingent, in which one product has a distinct utility even in the absence of other product(s) (bundled pricing; Venkatesh & Mahajan, 1993); (2) fully contingent, in which one product does not have a distinct utility in the absence of other product(s) (tied pricing; Whinston, 1990); and (3) partially contingent, in which one product is contingent on some products, but not on other products (add-on pricing; e.g., Yu et al., 2011). The launch timing consists of (1) simultaneous (prices of multiple products are decided simultaneously) and (2) sequential (some prices are decided sequentially). Pricing literature has paid much attention to the simultaneous or sequential pricing for non-contingent products. For example, Amazon can set a new (discounted) price for an existing or new product after consumers have already purchased a particular product, the so-called reserved product pricing (Prasad, Venkatesh, & Mahajan, 2015). However, pricing literature lacks sufficient research on sequential pricing strategies for not only fully contingent products between the base and add-on products but also partially contingent products among multiple add-on products, which are prevalent in the mobile app market.

Research in pricing does suggest that the base and add-on pricing practices can increase firms' overall profits (Yu et al., 2011; Wu et al., 2013). Yet, scholars have long argued that price plays not only an informative role—signaling product quality (Rao & Monroe, 1989) and performance (Dodds, Monroe, & Grewal, 1991)—but also an allocative role—allocating available monetary resources across multiple products (Erickson & Johansson, 1985). From the informative perspective, research suggests three potential sources in terms of consumers' response to price (Rao & Monroe, 1989; Völckner, 2008). First, consumers infer quality information from price, such that higher prices indicate higher quality and thus increase perceived utility (Kardes, Cronley, Kellaris, & Posavac, 2004). Second, consumers may perceive price as a surrogate indicator of prestige (Lichtenstein, Ridgway, & Netemeyer, 1993), which again results in a positive impact of price on purchase intention. Third, hedonistic consumption designates a customer behavior that relates to pursuing emotional responses associated with using a product, such as pleasure, excitement, and fun (Hirschman & Holbrook, 1982). In the mobile gaming market, purchasing add-on products can be regarded as hedonistic consumption due to the characteristics of enjoyment, fun, flow, or playfulness (Guo & Barnes, 2011; Han & Windsor, 2013).

Conversely, from the allocative perspective, consumers may place more weight on the price–sacrifice relationship when judging the value of the product (Erickson & Johansson, 1985). Research suggests that when consumers can process product information thoroughly, attributes other than price are more likely to be used in determining the quality of a product (Rao & Monroe, 1988). Moreover, consumers are likely to maintain mental accounts of their spending on different products, as well as individual products (Kahneman & Tversky, 1979; Thaler, 1985). In the mobile app market, mental accounts related to the base and add-on products mean that an increase in the price of a new add-on compared with those of the base or other add-ons increases the monetary allocation to the new add-on and reduces its perceived value. Evaluating an offered price's fairness or unfairness consists of comparing this price with a transaction reference, usually the most recent or the average transaction (Kahneman, Knetsch & Thaler, 1986; Monroe & Lee, 1999). Mobile app consumers are likely to perceive the new add-on price as cheap or expensive after comparing it with the reference price of the base or add-on product. As such, consumers may exhibit little satisfaction with perceived price unfairness when paying higher prices for sequentially marketed add-ons (Ellison, 2005; Gabaix & Laibson, 2006).

Although this line of thinking assumes that informative and allocative roles of add-on price may affect sales differently, some pricing studies have examined that varying prices over time may be caused by the need for attracting uninformed consumers (Villas-Boas & Villas-Boas, 2008), the scarcity of the products with regard to the number of buyers (Gershkov & Moldovanu, 2009) or network externalities (Cabral, Salant, & Woroch, 1999). On the mobile app market, app providers may set higher prices for high-performing add-on products (i.e., have higher sales or greater popularity) or lower prices for low-performing ones dynamically. However, this study focuses mainly on how base and add-on pricing strategies affect add-on sales (i.e., price–sales causality) rather than how add-on sales affect price changes (i.e., sales–price causality).

*2.2. The role of product popularity in evaluating add-on products*

Although price information plays a pivotal role in influencing the sales of digital products such as video games (Choi et al., 2018) and mobile apps (Kübler, Pauwels, Yildirim, & Fandrich, 2018), its effect can be contingent depending on the popularity of a product (Choi et al., 2018; Zhu & Zhang, 2010). In mobile app markets, base product consumers have high uncertainty about the quality of add-on products due to the unobservability of their popularity-related information. For example, the quantity of add-on products being sold is not publicly displayed in the app market. Product popularity, as the representative product-specific characteristic (Zhu & Zhang, 2010), is one of the primary factors that determines purchase decision (Chen, 2008; Duan, Gu, & Whinston, 2009).

The first form of product popularity is others' actions, and it affects consumers' purchase decision, in addition to imperfect individual information (e.g., price) (Sunder, Kim, & Yorkston, 2019). To minimize uncertainty about their own decisions, people often use information provided by others and converge on similar actions, the so-called herding behavior (Banerjee, 1992). Previous studies have examined online herding behavior in the context of digital auctions (Dholakia, Basuroy, & Soltysinski, 2002), software downloading (Hanson & Putler, 1996), online product choice (Huang & Chen, 2006), and board games (Sunder et al., 2019). In this study, we use base sales as the representative cue of action-based popularity information in mobile app markets (Cheung et al., 2014; Huang & Chen, 2006).

The second form of product popularity is consumer reviews; it influences consumers' purchase decisions because millions of consumer reviews often represent aggregate consumer preference data (Decker & Trusov, 2010). Numerous studies have suggested that the volume of consumer reviews, indicating a product's popularity and credibility, is significantly related to product sales (e.g., Duan et al., 2008; Godes & Mayzlin, 2004; Jang & Chung, 2015; Liu, 2006). Hence, we use review volume as the representative cue of opinion-based popularity information in mobile app markets (Chen, 2011; Cheung et al., 2014; Huang & Chen, 2006). When a base product is more popular than others, this information may help consumers attribute higher add-on price to higher quality, thereby mitigating perceptions of a higher relative price (Bolton, Warlop, & Alba, 2003).

## 3. Hypotheses development

### *3.1. The effect of inter-price relationship on add-on sales in mobile games*

When mobile game consumers choose between options (e.g., add-ons), they tend to make a choice based on both absolute and relative values (Vlaev et al., 2011). In some cases (e.g., when a consumer faces or has bought 20 add-on options), the quality of add-ons is difficult to judge, and comparisons with other add-ons are not easy. It is argued that the human capacity for processing a sequence of stimuli (e.g., add-ons) is limited to approximately seven items (Miller, 1956). Here, we presume that price plays an informative role—better add-ons are more highly priced—and consumers tend to make absolute judgments about the value of each add-on (Rao & Monroe, 1989). In other cases (e.g., when a consumer only bought a base product and two add-ons), price information for both the base product and comparable add-ons is salient. This triggers price comparison when consumers can make relative comparisons between the new add-on's price and base price or among other add-ons (Dodds, Monroe, & Grewal, 1991; Matthews & Stewart, 2009). Figure 1 illustrates how consumers reflect absolute and relative aspects of the new add-on price on their purchase decisions: the absolute price itself and the relative size of the price.

[Insert Figure 1 about here]

In the absolute context (Case 1), purchasing add-ons in mobile games is regarded as a hedonic, experiential behavior (Han & Windsor, 2013), and therefore, justifying the purchase situations is difficult (Chitturi, 2009). In the hedonic consumption, the higher new add-on price indicates higher quality and thus increases perceived utility (Kardes et al., 2004). Favorable perceptions of higher prices are based on the price cue signals to the purchasers in terms of their own thoughts and feelings associated with using the product (Völckner, 2008). Furthermore, research suggests that consumers may choose the risky options (e.g., the purchase of higher-priced add-ons) for which they expect to feel better on average (Mellers, Schwartz, Ho, & Ritov, 1997), and the maximization of hedonic experience makes pre-rational decisions (Finucane, Peters, & Solvic, 2003). As the quality of each add-on in mobile games will directly affect consumers' perceived value (Guo & Palatla, 2015), we expect mobile game consumers to regard a high-priced add-on as a higher-quality product when the absolute price information is considered (i.e., more emphasis on informative aspects). Hence, this study hypothesizes the following:

**H1.** The absolute price of a new add-on in mobile games has a positive effect on its sales.

Conversely, in a situation where consumers evaluate the relative price information of a new add-on, compared with the base product (Case 2) and other add-ons (Cases 3 and 4), within the same product, consumers naturally increase their focus on comparative judgments—the most recently-purchased item is a point of reference for the current judgment—relative to absolute judgments (Matthews & Stewart, 2009). Because consumers have rational expectations about add-ons, they will correctly infer the prices of the purchased products in any pure strategy equilibrium (Ellison, 2005; Shulman & Geng, 2019). By the time consumers compare the price of a new add-on with those of other existing products, they will focus more on allocative aspects by creating mental accounts of the previously purchased base and/or add-on products (Erat & Bhaskaran, 2012; Matthews & Stewart, 2009). Furthermore, consumers are likely to consider past prices as a reference point when judging the fairness of the new add-on price (Bolton et al., 2003). Therefore, we expect that if the mobile game's new add-on price is higher (lower) than the base or other add-on prices (i.e. the reference price), consumers of the game will have lower (higher) purchase intentions for the new add-on due to the negative feasibility concerns (Guo & Papatla, 2015). Hence, we hypothesize the following:

**H2.** The relative price of a new add-on in mobile games, compared with the price of a base product, has a negative effect on its sales.

**H3.** The relative price of a new add-on in mobile games, compared with the prices of existing add-ons, has a negative effect on its sales.

*3.3. The effect of base sales on add-on sales in mobile games*

According to the theory of herding behavior (Banerjee, 1992), consumers prefer popular products or follow the crowd, which represents a positive social cue (DeSarbo, Kim, Choi, & Spaulding, 2002). Informational cascades often occur in uncertain situations in which people describe their preferences sequentially and the value of the outcome is relatively difficult to determine (Bikhchandani, Hirschleifer, & Welch, 1992). Online consumers are sensitive to sales volume because others' purchase actions provide an informative signal of quality that encourages potential customers to follow the actions of their predecessors and eventually make purchase decisions (Bonabeau, 2004). Previous studies have demonstrated that consumers tend to select bestseller books (Bonabeau, 2004; Huang &

Chen, 2006), most downloaded software programs (Duan et al., 2009; Hanson & Putler, 1996), and most peer-bought beauty products (Cheung et al., 2014). In the mobile gaming context, when the volume of base game sales is displayed in the market, this popularity information can be used to indicate both quality and preference and assist consumers in making good decisions on purchasing add-ons for the mobile game.

Although the relative price of a new add-on may represent price unfairness and thus negatively influence its sales, the degree of the relationship would depend on the level of base sales. Research on video games shows that the high price of more (less) popular products has a positive (negative) impact on their sales (Choi et al., 2018; Zhu & Zhang, 2010). This suggests that although consumers consider the higher relative price of a new add-on as unfair, they are likely to accept the high-priced add-on when the base product has a higher sales volume. That is, the negativity of higher add-on price than base or other add-on product prices can be attenuated by signaling its superior quality endorsed by the higher volume of base sales. We propose the following hypothesis:

**H4.** Base sales attenuate the negative effect of the relative price of a new add-on in mobile games, compared with the prices of (a) base product and (b) existing add-ons, on its sales.

*3.4. The effect of review volume on add-on sales in mobile games*

In the online environment, information from others' reviews is considered more persuasive and trustworthy (Ba & Pavlou, 2002). Online consumer reviews can be decomposed into volume, valence, and content (Jang, Chung, & Rao, 2020). Although the review valence signals the overall product quality (Kostyra et al., 2016), its effectiveness has yielded inconsistent findings. Jang et al. (2020) found that the review volume of product quality and ease-of-use drives more sales than the valence, whereas the review valence of product innovativeness and price outperforms the volume. However, most existing studies suggest a positive effect of review volume because the volume can signal consumers' enthusiasm for the product (Duan, Gu, & Whinston, 2008) and elicit consumers' interest and product awareness (Chen, Wu, & Yoon, 2004). In this study, we focus on review volume as the representative signal of product popularity (Choi et al., 2018; Zhu & Zhang, 2010).

Previous studies have mixed views on the effect of the volume of consumer reviews on market outcomes. Some studies demonstrate that review volume can indicate a product's popularity and credibility because it represents the number of customers who have bought the product (Park, Lee, & Han, 2007). Other studies show that review volume has no effect on the sales of cell phones (Gopinath, Thomas, & Krishnamurthi, 2014) and box office (Chintagunta, Gopinath, & Venkataraman, 2010). This may be explained by the fact that a large number of reviews can create information overload for potential customers (Park & Lee, 2008). In the context of digital goods, research has demonstrated that the volume of consumer reviews has a positive impact on the sales of video games (Zhu & Zhang, 2010) and mobile games (Jang & Chung, 2015; Jang et al., 2020). Furthermore, more information from consumer reviews can reduce base product consumers' uncertainty about add-ons and strengthens their confidence in add-ons, eventually leading to a greater willingness to pay for them (Brynjolfsson & Smith, 2000).

As discussed in H4, we expect the negativity of new add-ons' relative price on their sales is moderated by product popularity that is indicated by the volume of consumer reviews. As consumers have heterogeneous attention and reaction to price information (Dickson & Sawyer, 1990), the signal value of review information will affect consumers' consideration of add-on price information (Kostyra et al., 2016), which further affects their purchase decision on add-on products (Jang & Moutinho, 2019). Specifically, the negative effect of price unfairness, driven by a higher add-on price than the base and other add-on product price, on add-on sales can be attenuated when the base product has more consumer reviews (Choi et al., 2018; Zhu & Zhang, 2010). Thus, we propose the following:

**H5.** Review volume attenuates the negative effect of the relative price of a new add-on in mobile games to (a) base product and (b) existing add-ons on its sales.

Based on the aforementioned theoretical foundations, we concentrate on the effects of absolute and relative prices of new add-on products, compared with base and existing add-on products, on their sales with a contingency consideration of base sales and review volume. Figure 2 depicts the proposed research model and outlines the research hypotheses, which will be discussed in greater detail subsequently.

[Insert Figure 2 about here]

## 4. Method and analysis

### *4.1. Empirical setting and data collection*

To test our hypotheses, we obtained the base and add-on pricing and sales data of mobile games from a leading mobile app market in Asia. Like other studies (Shulman & Geng, 2019), we focused on mobile games among the app categories because they occupy the most revenue-generating category, totaling 77% in 2018 (Iqbal, 2019). In addition, mobile games are composed of a platform of base and add-on products, and game developers commonly develop and commercialize multiple add-ons during a product life cycle (Jang & Chung, 2015). Therefore, it would be crucial for mobile game developers to build an optimal pricing strategy for multiple add-ons that can be launched simultaneously with the base product or sequentially after the base product launch.

With help from the mobile app market, a dataset of pricing actions, base and add-on sales, and product characteristics were collected for all mobile games launched between November 2010 to August 2011. We need to examine the sales effect of inter-price relationship among the base and multiple add-on products. Hence, we excluded base products with zero or one add-on; all mobile games should have at least two add-ons. The final sample of 7,108 observations consisted of pricing and sales transactions generated from 74 base products and 514 add-on products. We found that the observation periods for each add-on product varied from 1 week to 42 weeks. Specifically, 25% of in-app purchase transactions in this sample had less than 4 weeks of product lifetime, and 75% of them had less than 15 weeks. The average lifetime of 10.43 weeks implies that mobile games were extremely competitive and had a relatively short life cycle.

Furthermore, we found that all game developers in this sample set the same price for each base and add-on product during the product life cycle. Due to the short life cycles of mobile games, developers priced and launched base games and add-ons in the marketplace without price changes although they could conduct price promotions (e.g., coupons and discounts). This means that absolute and relative prices of new add-ons influence consumers' judgment about the price levels and their purchase decisions, which naturally control for the reversal effect in our data (i.e., firms may change add-on prices dynamically depending on the add-on sales). Hence, this empirical setting enables us to examine the causal relationship between absolute and relative prices of add-on products and their sales.

### *4.2. Measurements and equation*

We used the number of weekly downloads of each add-on product to measure its sales volume, which is the dependent measure for our study *Sales* (Jang & Chung, 2015; Jang et al., 2020; Zhu & Zhang, 2010). The main independent variables include absolute and relative prices. For the absolute price variables, we considered the dollar amounts of a base product's price (*BasePrice*), a new add-on's price (*NewAddonPrice*), and existing add-ons' prices (*ExistingAddonPrice*). Although base product consumers might or might not have purchased all or some of the existing add-ons, we assume that they will have the external reference price by comparing revealed prices of existing add-ons (e.g., average, minimum, or maximum prices). The average price of existing add-ons was empirically chosen for this study after the model comparison was tested. Two relative price variables of a new add-on were calculated using absolute price information. One is the relative price compared with the price of a base product (*RelativePriceBase*), which is measured by dividing *NewAddonPrice* by *BasePrice*. The other is the relative price compared with the price of existing add-ons (*RelativePriceAddon*), which is measured by dividing *NewAddonPrice* by *ExistingAddonPrice*.

As the product popularity variables, we initially measured four types of variables to consider 2 (base sales and consumer reviews) × 2 (weekly and cumulative) situations. In this study, weekly popularity measures were considered because mobile apps are extremely competitive categories (Guo & Papatla, 2015) and have a relatively short life cycle (Jang & Chung, 2015). Meanwhile, weekly base sales volume was measured by the number of mobile game downloads in week $t$, and cumulative base sales volume was measured by the number of cumulative downloads until week $t-1$. In the same vein, weekly and cumulative review volumes were measured by the number of consumer reviews in week $t$ and the number of cumulative reviews until week $t$-1, respectively. However, we selected only two variables, *WeekBaseSales* and *WeekReviewVolume*, due to the multicollinearity among the four variables. This combination enables us to investigate whether immediate popularity information (i.e., weekly base sales and weekly review volume) moderates the relationship between relative add-on price and add-on sales (Healey & Moe, 2015; Jang & Chung, 2015).

Finally, we controlled for substantial heterogeneity of mobile games in terms of product characteristics because such differences not only affect how consumers assess products (Swaminathan, 2003) but also reduces the likelihood of systematic correlation between prices and omitted variables (Guo & Papatla, 2015). Specifically, we included the following variables: (1) the number of software upgrades (e.g., adding new features) of the mobile app released from its launch to week $t$−1 (*Upgrades*); (2) the number of add-ons bound with the base product until week $t-1$ (*AddonNumber*); (3) the sequence of a new add-on for the base product (*AddonSequence*); (4) *Size* in megabytes; and (5) genre of the mobile game: action, arcade, role playing, puzzle, shooting, and sports. We used puzzle as the baseline and represented the other five genres by five dummy variables, namely, *Action*, *Arcade*, *Roleplaying*, *Shooting*, and *Sports* (Guo & Papatla, 2015; Jang & Chung, 2015).

For the analysis, we developed the following empirical model including all the variables:

$$\begin{aligned} LnSales_{j,t} = {} & \beta_0 + \beta_1 BasePrice_{j,t} + \beta_2 AddonPrice_{j,t} + \beta_3 ExistingAddonPrice_{j,t} \\ & + \beta_4 RelativePriceBase_{j,t} + \beta_5 RelativePriceAddon_{j,t} \\ & + \beta_6 RelativePriceBase * WeekBaseSales_{j,t} \\ & + \beta_7 RelativePriceAddon * WeekBaseSales_{j,t} \\ & + \beta_8 RelativePriceBase * WeekReviewVolume_{j,t} \\ & + \beta_9 RelativePriceAddon * WeekReviewVolume_{j,t} \\ & + \beta_{10} Upgrades_{j,t-1} + \beta_{11} AddonNumber_{j,t-1} \\ & + \beta_{12} AddonSequence_{j,t} + \beta_{13} Size_j + \beta_{14} Action_j + \beta_{15} Arcade_j \end{aligned}$$

$$+\ \beta_{16}Roleplaying_j\ +\ \beta_{17}Shooting_j\ +\ \beta_{18}Sports_j\ +\ \varepsilon_j$$

where $LnSales_{j,t}$ denotes the log-transformed sales volume of add-on product $j$ on week $t$ and $\varepsilon_j$ is the error term of the model.

## 5. Results

### *5.1. Descriptive statistics*

Table 1 contains the descriptive statistics and correlation coefficients for the variables. In our sample, the average sales of individual add-on product per week are 3,939, and the average price of base products, ranging from \$0.229 to \$11.364, is \$2.992, which is higher than those of new add-on products (\$2.056), ranging from \$0.091 to \$50, and existing add-on products (\$2.183), ranging from \$0.166 to \$14.214. Mean differences between the base and new add-on price samples [$t(7,107) = 17.052$, $p < 0.01$], between base and existing add-on price samples [$t(7,107) = 20.998$, $p < 0.01$], and between new and existing add-on price samples [$t(7,107) = -2.747$, $p < 0.01$] are statistically significant. From the perspective of inter-price relationships in a mobile game, the average ratio of the add-on price to the base price is 1.09, and the ratio of the new add-on price to the existing add-on price is 1.13. These values indicate that newly launched add-ons are slightly more expensive than previously launched products such as base product and existing add-ons.

Regarding product popularity, the average volume of weekly base sales is 829 and the average volume of cumulative consumer reviews is 1,494. On average, mobile games in this sample have 5.3 software upgrades, 12.58 add-ons, and 13.308 megabytes. The mobile games are distributed as follows: puzzle genre (46%), role playing (25%), arcade (12%), sports

(7%), action (5%), and shooting (5%). The correlations among the variables were relatively weak, except for the correlation between *NewAddonPrice* and *RelativePriceBase* (0.776). Thus, we detected the potential presence of multicollinearity by calculating the variance inflation factor (VIF), which ranged from 1.131 to 5.139, indicating that multicollinearity was not a serious problem in the final model.

[Insert Table 1 about here.]

*5.2. Hypothesis tests*

Table 2 presents the means and standard deviations of the parameter estimates. The result (Model 1) shows that the absolute price of a new add-on is positively related to its sale ($\beta_2$= 0.030, $p < 0.01$), thus supporting H1. Moreover, the absolute price of existing add-ons also has a positive effect on the new add-on sales ($\beta_3$= 0.023, $p < 0.01$). Meanwhile, the relative price level of a new add-on compared with the base price is negatively related to its sales ($\beta_4$= −0.242; $p < 0.01$), but its relative price has no relationship with that of the existing add-ons , thus supporting H2, but not H3. These results imply that although the absolute value of an add-on increases its sales, the higher relative price of the add-on in comparison with the price of the base product decreases the add-on sales.

[Insert Table 2 about here.]

When interaction terms between relative price and popularity information are added in the model, both positive and negative effects are shown. Specifically, if the base product is more popular due to a large customer base, the negative effect of the relative add-on price will be strengthened compared with the base product ($\beta_6$= −0.139, $p < 0.01$) but attenuated compared with existing add-ons ($\beta_7$= 0.063, $p < 0.01$). This result supports H4b, but not H4a. In addition, the review volume-driven product popularity attenuates the negative effect of the relative add-on price compared with existing add-ons ($\beta_9$= 0.138, $p < 0.05$), but not compared with the base product prices. This result also supports H5b, but not H5a. Interestingly, both the base sales and review volume are found to play a critical role in reducing the negativity of an add-on's relative price compared with existing add-ons rather than its relative price compared with the base price.

Furthermore, this study offers supplementary results concerning the effects of product characteristics on add-on product sales. The number of software upgrades in the mobile game has a positive effect, suggesting that continuous product improvement attracts more add-on sales (Jang & Chung, 2015). The number of add-on products within the same mobile game also has a positive effect on add-on sales, which suggests that various add-on features are likely to increase individual add-on sales. Consumers more preferred add-on products that are sequenced or launched in the early stage than those in the later stage due to consumer exposure to early-encountered add-on products (Niedrich & Swain, 2008). In addition, we find that the software size of a mobile game has a negative effect on add-on product sales, indicating that smaller game apps attract more add-on sales. Finally, the estimated effects of the game genres suggest that action, role playing, shooting, and sports games have more positive effects than puzzle games.

Finally, the robustness of our analysis was checked by testing an alternative model (Model 2) by removing mobile apps with the highest and lowest sales volume (i.e., 3.14% of the total observations) and assessing whether findings of the alternative model are similar to those of the main model. The results show that the model performance has improved slightly (Adjusted $R^2$: 0.373 versus 0.371), but the overall results are consistent with those presented in Model 1. One exception is that the absolute price of existing add-ons has no relationship with the add-on sales. Hence, we find that our key hypotheses are robust under the circumstance with non-extreme apps.

## 6. Discussion and Implications

Given the important revenue source in the mobile app market, understanding how to monetize new add-ons for a given product line (i.e., base and add-on products) remains important. One of the basic decisions confronting app developers when launching a new add-on is how much price should be set toward existing base product users with a consideration of the product's popularity. Indeed, it is relevant for both mobile app researchers and practitioners to understand how price and non-price information influences the add-on sales separately and interactively. This study investigated the importance of strategic pricing for add-on products to maximize their sales in the mobile gaming market. Specifically, it empirically examined how absolute and relative price information of newly launched add-on affects its sales and how the price–sales relationship varies across two types of product popularity (i.e., base sales and consumer reviews). This study finds that the higher absolute price of an add-on may signal higher quality, but its relative price compared with the base price influences its sales negatively. In addition, product popularity, such as base sales and review volume, attenuates the negativity of the higher new add-on price than the previously launched add-on price.

### *5.1. Theoretical implications*

This study has several important theoretical contributions to the add-on pricing literature, especially for the base and add-on product system, in general, and mobile apps, in particular (Guo & Papatla, 2015; Shulman & Geng, 2019). First, this study contributes to the identification of optimal add-on pricing strategies for (1) fully contingent (between base and add-ons) and (2) partially contingent (among multiple add-ons) products that a firm launches sequentially in the market. Mobile apps are an appropriate case because the app and in-app purchases are fully contingent, multiple in-app purchases are partially contingent, and in-app purchases can be offered sequentially over a product life cycle. Prior research on add-on pricing focuses on either conceptual (Ellison, 2005) or analytical (Shulman & Geng, 2013; 2019) modeling and considers the effect of base and add-on prices on consumer ratings (Guo & Papatla, 2015). This study, to date, is the first to empirically demonstrate how price (absolute vs. relative; base vs. add-on) and non-price (product popularity) information affects the sales of add-on products.

Second, our empirical study does support the theorizations and hypotheses regarding the absolute and relative contexts of add-on price information in the product structure of the base and multiple add-on products. From the absolute price perspective, this study confirms that mobile app consumers are likely to put more emphasis on the informative aspects when the absolute add-on price is evaluated. That is, mobile in-app purchases can increase the enjoyment of mobile apps, resulting in consumers' willingness to purchase high-priced add-ons (Hamari, 2015). However, from the relative price perspective, our findings indicate that mobile app consumers tend to put more emphasis on the allocative aspects when the relative price information is evaluated. In this context, because consumers have recently paid for the base or add-on product(s), they tend to consider those prices as a reference point and comparatively judge the price of a new add-on (Bolton et al., 2003; Dodds et al., 1991; Erat & Bhaskaran, 2012; Matthews & Stewart, 2009). Our findings empirically confirm the existence of duality aspects (informative vs. allocative) of add-on price information, depending on the absolute and relative contexts, respectively.

Finally, this research reveals that base sales and review volume both play a critical role in increasing the sales of an add-on product. Previous studies have mainly examined the direct effects of base sales (Healey & Moe, 2015) or consumer reviews (Kübler et al., 2018) separately. This study extends the existing literature by focusing on the moderating effect of two popularity cues on the relationship between add-on price and sales. Our finding shows that higher product popularity cues, in terms of base sales and review volume, reduce the negativity of the relative price of a new add-on compared with the base product rather than compared with the existing add-on price(s). A possible explanation is that the observable base price makes consumers more sensitive to add-on prices than unobservable add-on prices. For a more popular product, consumers are more favorably disposed toward the price unfairness between a new add-on and the base product because the purchase of popular products tends to elicit a positive social cue (DeSarbo et al., 2002). Conversely, for less popular products, consumers tend to be more price-conscious of add-ons (Zhu & Zhang, 2010), thereby decreasing their willingness to purchase add-ons.

### *5.2. Managerial implications*

This study provides useful managerial implications in the field of mobile app marketing. App developers may sell their base apps at relatively low or zero prices, which are posted in the product description, and subsequently earn substantial revenue from in-app purchases, whose prices are often shrouded ("freemium add-on pricing") (Wu et al., 2013). However, this study finds that although consumers prefer high-priced (high-quality) add-ons, they care about the inter-price relationship among base and add-on products when making purchase decisions. Recently, Apple App Store and Google Play require more scrolling to find in-app purchase prices (Murphy, 2018). Hence, if app developers regard add-ons as the primary revenue source, managers should consider the relative price of add-ons that are launched during the product life cycle. Our empirical findings suggest that, for developing and pricing base and add-on products, app providers may set higher base price (with high-quality functionalities) and offering relatively lower add-on prices subsequently ("paymium add-on pricing").

Furthermore, app developers should understand that base product consumers tend to evaluate product popularity cues, as well as price cues, when making purchase decisions on add-ons. Depending on base sales and review volume, managers should be cautious with their add-on pricing strategy because users' price sensitivity varies across different inter-price relationships among base and add-on products. Our findings suggest that two popularity cues are more salient at the later stage when established users consume multiple add-ons than at the early stage when users are newly exposed to add-on packages. These findings provide mobile app marketers with the following three-staged pricing strategies for base and add-on products that can maximize their revenue from the add-on sales: (1) launching high-quality (high-priced) base app at the early stage, which increases the base sales; (2) launching high-quality add-ons with relatively lower prices at the middle stage, which encourages consumers to generate positive reviews; and (3) launching medium quality add-ons with higher prices at the later stage, which increases the total revenue.

## 7. Limitations and future research

Although this research offers important theoretical and managerial implications, there are some limitations. First, the analyses and results of this study are based on observational data in a mobile app market. Although the fixed prices of base and add-on products during their life cycles were observed in the natural setting, the observation data have an inherent limitation with drawing a claim of causality (i.e., the effect of absolute and relative price information on add-on sales). Therefore, future research needs to incorporate multiple methods of approach to triangulation (e.g., observational and experimental data) to cross-check the validity of our findings.

Second, to support the claims for the price–sales causal relationships, additional analyses should be performed to demonstrate whether the observed findings hold under various conditions, in particular, low-priced base products and high-priced base products. Due to the multicollinearity concerns among certain variables in segmented samples (e.g., low-priced and high-priced product groups), this study failed to run various robustness analyses. Research has found that consumers' willingness to buy add-on products can be influenced by product quality (e.g., greater enjoyment from a high-priced base game may reduce willingness to purchase add-ons) (Hamari, 2015). Hence, it is fruitful to study how consumers respond to the inter-price relationships depending on different product categories (e.g., better-performing and less-performing products).

Third, although the measurements for base product characteristics are comprehensive, this study excluded measurements for add-on product characteristics because we could not classify the add-on products into different types due to lack of information. Add-ons can be characterized as "alignable" when the add-on enhances an existing feature of the base product or "nonalignable" when the add-on introduces a new capability (Bertini, Ofek, & Ariely, 2009). Research indicates that alignable add-ons influence evaluation by shifting the reference level of the attributes related to the add-on products, whereas nonalignable add-ons do so by cueing a general inference about the overall product value (Bertini et al., 2009). Therefore, future research could classify add-on products into different levels of alignment and the effectiveness of inter-price relationships among base and add-on products.

Finally, this study used the volume information of consumer reviews as a measure of opinion-based product popularity. However, researchers have examined the importance of the valence information (e.g., positive and negative ratings) and content (e.g., functional and emotional expressions) in the digital gaming market (Jang & Chung, 2015; Jang et al., 2020; Zhu & Zhang, 2010). Future research should examine the moderating role of review valence and specific contents as well as review volume, in the price-sales relationship.

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**Table 1.** Descriptive statistics of variables in the data.

| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) | (17) | (18) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) *lnSales* | 1 | | | | | | | | | | | | | | | | | |
| (2) *BasePrice* | .022 | 1 | | | | | | | | | | | | | | | | |
| (3) *NewAddonPrice* | −.055** | −.008 | 1 | | | | | | | | | | | | | | | |
| (4) *ExistingAddonPrice* | .063** | −.012 | .381** | 1 | | | | | | | | | | | | | | |
| (5) *RelativePriceBase* | −.066** | −.247** | .776** | .257** | 1 | | | | | | | | | | | | | |
| (6) *RelativePriceAddon* | −.086** | .004 | .582** | −.128** | .475** | 1 | | | | | | | | | | | | |
| (7) *WeekBaseSales* (unit: thousands) | .183** | −.012 | −.031** | .056** | −.058** | −.028* | 1 | | | | | | | | | | | |
| (8) *WeekReviewVolume* (unit: thousands) | .042** | .091** | .254** | .472** | .061** | −.011 | .195** | 1 | | | | | | | | | | |
| (9) *Upgrades* | .186** | −.084** | .147** | .279** | .093** | .02 | .120** | .177** | 1 | | | | | | | | | |
| (10) *AddonNumber* | −.101** | −.032** | −.131** | −.248** | −.155** | −.041** | −.090** | −.063** | −.279** | 1 | | | | | | | | |
| (11) *AddonSequence* | −.070** | .025* | −.046** | −.152** | −.077** | .036** | −.019 | −.038** | .002 | .452** | 1 | | | | | | | |
| (12) *Software* | −.081** | −.120** | −.055** | −.067** | −.094** | −.025* | .071** | .097** | −.078** | .268** | .098** | 1 | | | | | | |
| (13) *Action* (dummy) | −.004 | −.079** | .116** | .174** | .115** | .026* | .098** | −.017 | .071** | −.173** | −.109** | .026* | 1 | | | | | |
| (14) *Arcade* (dummy) | −.036** | −.183** | −.028* | −.008 | −.018 | −.027* | .069** | −.043** | −.065** | .024* | −.040** | −.257** | −.085** | 1 | | | | |
| (15) *Puzzle* (dummy) | −.160** | .014 | −.015 | −.078** | −.051** | −.001 | −.187** | .015 | −.132** | .237** | .076** | .077** | −.206** | −.346** | 1 | | | |
| (16) *Roleplaying* (dummy) | .120** | .162** | −.01 | .005 | .047** | .006 | −.091** | −.044** | .028* | −.152** | −.051** | −.086** | −.131** | −.219** | −.534** | 1 | | |
| (17) *Shooting* (dummy) | −.029* | .015 | −.068** | −.119** | −.072** | −.018 | −.041** | −.024* | −.106** | −.074** | −.090** | .155** | −.049** | −.082** | −.199** | −.126** | 1 | |
| (18) *Sports* (dummy) | .178** | −.013 | .040** | .102** | .003 | .019 | .376** | .134** | .317** | −.029* | .151** | .177** | −.063** | −.105** | −.256** | −.163** | −.061** | 1 |
| Mean | 3.939 | 2.992 | 2.056 | 2.183 | 1.090 | 1.130 | 0.829 | 0.124 | 5.300 | 12.580 | 9.000 | 13.308 | 0.050 | 0.120 | 0.460 | 0.250 | 0.050 | 0.070 |
| Minimum | 0.001 | 0.229 | 0.091 | 0.166 | 0.008 | 0.007 | 0.001 | 0 | 1 | 1 | 1 | 2.049 | 0 | 0 | 0 | 0 | 0 | 0 |
| Maximum | 66.941 | 11.364 | 50.000 | 14.214 | 27.500 | 10.714 | 16.531 | 5.762 | 39 | 36 | 72 | 53.675 | 1 | 1 | 1 | 1 | 1 | 1 |
| Standard deviation | 2.074 | 2.098 | 4.104 | 2.450 | 2.322 | 1.312 | 1.471 | 0.478 | 4.687 | 10.453 | 10.764 | 9.446 | 0.214 | 0.330 | 0.498 | 0.435 | 0.207 | 0.259 |

** $p < 0.01$, * $p < 0.05$.

**Table 2.** Estimated parameters of the model.

| Variable | Model 1 (Hypothesis testing) | | Model 2 (Robustness check) | |
|---|---|---|---|---|
| | Estimate | Standard error | Estimate | Standard error |
| (Intercept) | 3.456** | 0.081 | 3.687** | 0.079 |
| *BasePrice* | −0.005 | 0.011 | −0.017 | 0.010 |
| *NewAddonPrice* | 0.030** | 0.011 | 0.043** | 0.010 |
| *ExistingAddonPrice* | 0.023** | 0.011 | 0.017 | 0.011 |
| *RelativePriceBase* | −0.242** | 0.016 | −0.254** | 0.015 |
| *RelativePriceAddon* | −0.002 | 0.022 | −0.020 | 0.021 |
| *RelativePriceBase* × *WeekBaseSales* | −0.139** | 0.015 | −0.135** | 0.014 |
| *RelativePriceAddon* × *WeekBaseSales* | 0.063** | 0.015 | 0.062** | 0.014 |
| *RelativePriceBase* × *WeekReviewVolume* | −0.027 | 0.030 | −0.040 | 0.029 |
| *RelativePriceAddon* × *WeekReviewVolume* | 0.138* | 0.067 | 0.136** | 0.065 |
| *Upgrades* | 0.091** | 0.005 | 0.086** | 0.005 |
| *AddonNumber* | 0.014** | 0.002 | 0.008** | 0.002 |
| *AddonSequence* | −0.044** | 0.002 | −0.040** | 0.002 |
| *Size* | −0.035** | 0.002 | −0.032** | 0.002 |
| *Action* | 0.987** | 0.098 | 0.908** | 0.094 |
| *Arcade* | 0.185** | 0.066 | 0.219** | 0.065 |
| *Roleplaying* | 1.915** | 0.050 | 1.817** | 0.049 |
| *Shooting* | 1.816** | 0.100 | 1.651** | 0.096 |
| *Sports* | 2.633** | 0.087 | 2.519** | 0.084 |
| F statistic | 233.438 | | 228.127 | |
| $R^2$ | 0.372 | | 0.374 | |
| Adjusted $R^2$ | 0.371 | | 0.373 | |
| N | 7,108 | | 6,885 | |

** $p < 0.01$, * $p < 0.05$.

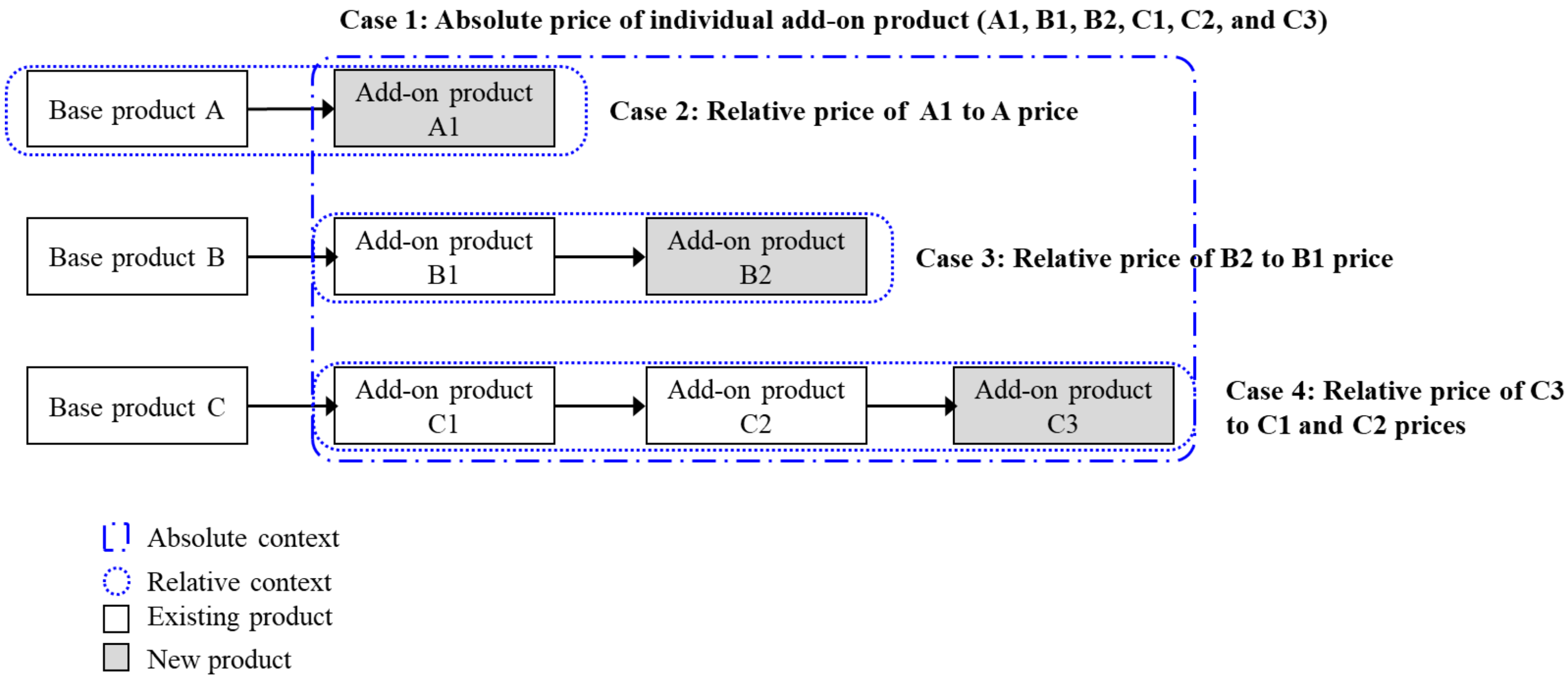


**Figure 1.** Absolute and relative aspects of add-on price information.

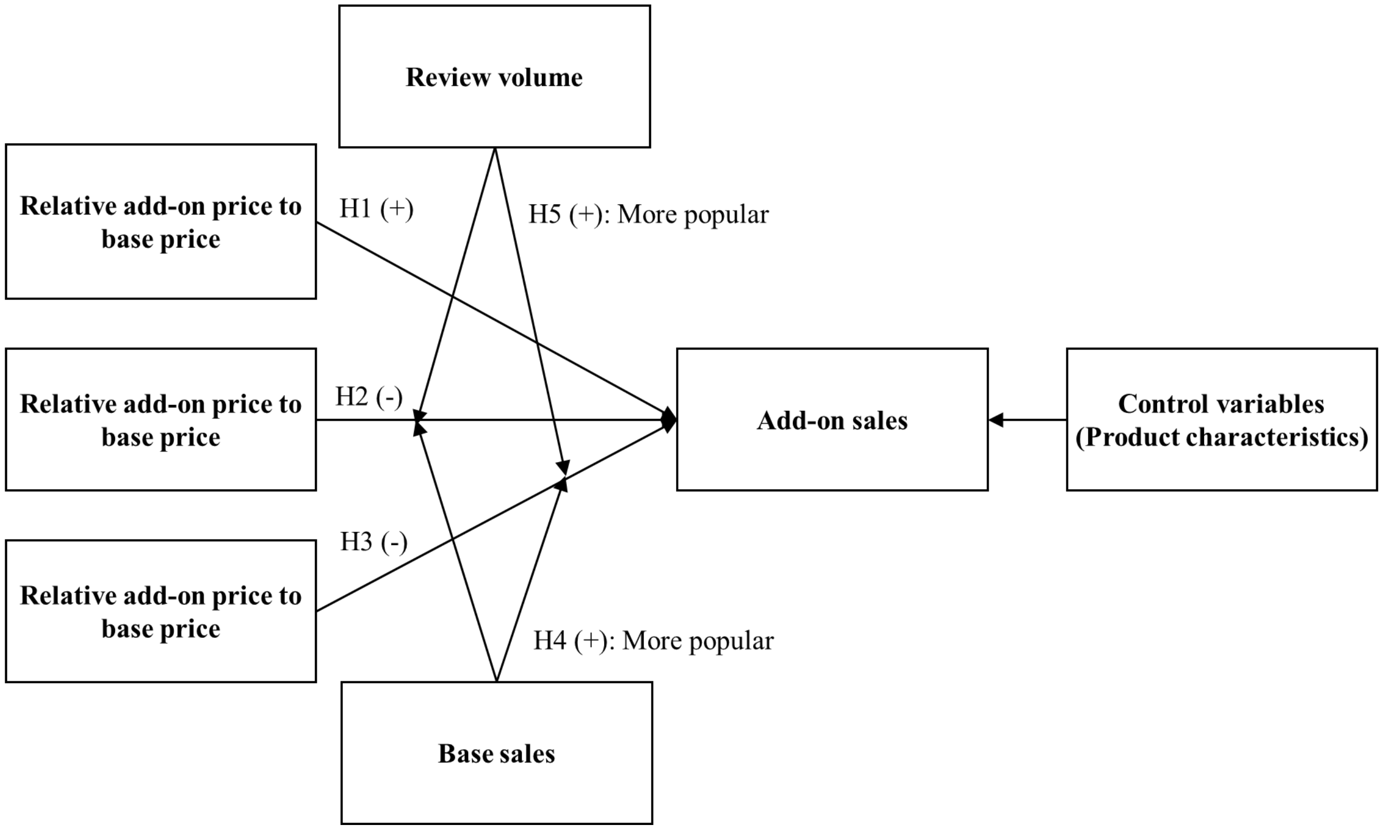


**Figure 2.** Research model.