Composite Model of Marketing Mix and Brand Equity for Purchasing Motorcycles

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Abstract

The current study investigates the effect of a composite model of the marketing mix and brand equity on motorcycle purchase decisions. For second-order, the marketing mix and brand equity were constructed using a disjointed two-state approach and a formative-formative weighting scheme. The purchasing decision was measured as a latent variable using a consistent partial least square (PLSc) model. The data was collected from 148 people who have bought motorcycles in Thailand. The results show that the lower-order constructs demonstrate how well they are organized by the indicators, as determined by the model fit indexes. To begin, the hypothesis regarding the three model fitting indexes is rejected. Thus, all bias indicators with shallow values and a negative symbol were removed from the composite model. Furthermore, multicollinearities exist between PLACE indicators, and they are addressed by removing the indicator with the highest variance inflation factors (VIF). Concerning purchasing decisions, the PLSc model with an indicator loading of less than 0.708 was eliminated. As a result, all three total model fit hypotheses returned to be accepted. For the higher-order construct, the composite model created a marketing mix positively linked to brand equity and purchasing decisions, and brand equity positively correlates with purchasing decisions. The hybrid model can generate model fit indexes for both the first and second construct.

Keywords: Marketing mix, Brand equity, Purchase decision, Composite model, PLSc model

Introduction

Motorcycles are widely used in Thailand, the fifth-highest in the world after India (18.5-24.5), China (15.5-21.5), Indonesia (6-8), and Vietnam (3-5) in millions of units in 2018. The brands Honda and Yamaha have market shares in Thailand that are now around 78.37% and 15.09%, respectively (Yongpisanphob, 2019), indicating a distinct perception of the brand by the consumer. Brand equity influences a company's strategic and economic interests (Gil et al., 2007) while producing incremental expenses and benefits (Aaker, 2004). The marketing mix is a primary method to accurately define the best marketing strategy, helping the company decide on the proper marketing plan. Brand equity and marketing mix can improve decision-making, minimize risk, identify preferences, and boost consumer satisfaction (Farquhar, 1989). Famous brand names can generate higher sales, higher income, and more significant results, while the marketing mix is a powerful tool to differentiate the customers from each business field (Aghaei et al., 2014). Brand equity and the marketing mix are typically the basis for consumer purchasing decisions.

The current study uses the composite model. Since Mode A is an unmeasured common factor (Rönkkö & Everman, 2013), the measurement error is not entirely accountable. This can cause type I and II errors, leading to multiple biases, such as higher loading and lower path coefficient estimation (Kock, 2019). Consequently, the PLSc model was born to solve questions calculated as a common factor (Dijkstra & Henseler, 2015 a & b). Using a corrected reliability approach, however, PLSc leads to lower statistical power requiring bigger sample sizes than other methods (Kock, 2019). Although reflective brand equity (Kim & Ko, 2012; Tong & Hawley, 2009) and market mix (Yoo et al., 2000) analyzes commonly used formative model should use in principle, one whose components are determinants of brand equity and marketing mix. However, the causal-formative type model suggested by many scholars has been abandoned (e.g., Aguirre-Urreta et al., 2016; Benitez et al., 2020). Thus, brand equity (Henseler, 2017) and marketing mix also assume a design-construct that use a hierarchical component model (HCM) composite. This involves a disjointed two-stage approach (Becker et al., 2012) and formative-formative types of weighting scheme or the composite of composite model (Schuberth et al., 2020).

This study investigates the relationship between marketing mix, brand equity, and motorcycle purchasing decisions. The emergent variable was used for marketing mix and brand equity, while the latent variable was used for purchasing decisions. A strong brand enables firms to adhere to their customer commitments. Empathy is developed when a brand compares itself in terms of emotional responses. Consumers naturally flock toward well-known brands, so a business's brand is essential. When given the opportunity, individuals are quickly persuaded of the benefits of a new brand. Because strong brands are based on quality, they require a more diverse marketing mix. These traits may influence the purchasing decisions of customers. Brand equity may also affect customer purchasing decisions. As a result of an organization's efforts, its brand equity may expand. This study supplemented Jhantasana's (2019) study on the impact of brand loyalty and brand awareness on purchase decisions using PLSc. The research design for this study is cross-sectional observational analytic in nature, with data collected from a group of bikers who consented to participate using a questionnaire. The data for this research were analyzed using ADANCO software utilizing a partial least square structural equation model with composite and latent variables.

Literature review

Marketing mix

The marketing mix is the main challenge in effectively affecting decision-making and market-related components. It incorpores incoreporates_the core components in order to prepare and implement the marketing strategy cycle to retain, reward, and connect consumers. Contact extends to the consumer network, increasing recognition of the company brand and attracting interest, a basic concept of customer satisfaction. The marketing mix equals the entire revenue process, blending various products (Baron & Jones, 1991), and adding visible and intangible factors (Czinkota, 2000). Gronroos (1994) argues that it is the strategic market role of a product whose components will boost business competition. The marketing mix is critical to consumer value and satisfaction (Al Badi, 2018). A successful marketing mix should isolate the company's marketing from other companies and monetization approaches (Eavani & Nazari, 2012). Borden (1964) may be the first to use the term marketing mix and suggested it to Culliton (1948). Borden's original marketing mix included 12 elements: product planning, pricing, branding, distribution channels, personal sales, advertisement, packaging, promotion, display, physical handling, fact-finding, and analysis. Some authors have sought to sum them up into two (Frey, 1961), three (Lazer et al., 1973), and four elements (McCarthy, 1964). McCarthy (1964) grouped to Borden's 12 elements into four or 4Ps: product, price, promotion, and place. Some researchers suggested a different marketing combination in the 1980s, e.g., Booms and Bitner (1980) integrated 3 Ps (participants, physical evidence, and process) for services, while Kotler (1986) incorporated political power and public opinion. MaGrath (1986) suggested the 3 Ps (personal, physical, and process management), while Judd (1987) presented a fifth P (people). Baumgartner (1991) suggested 15 Ps, while Goldsmith (1999) suggested 8 Ps (product, price, place, promotion, participants, physical proof, process, and personalization). Some authors (e.g., Rafiq & Ahmed, 1995) advocate utilizing Booms and Bitner's (1980) 7Ps method to supplement McCarthy's 4Ps as the uniform marketing mix. However, Constantinides (2002) notes that consumers typically experience each of the 4P's unique effects depending on the day, time, and place. The 4Ps model's strength is that it provides a dynamic, practical marketing decision-making model and has long been useful in case study research in business schools (Jobber, 2001). The marketing mix element (Yoo et al., 2000), mainly the product, position, promotion, and after-sales services, significantly impact brand equity dimensions (Shamami & Kheiry, 2019). The marketing mix is made up of many elements that are defined by the organization's principal goals. The 4Ps are still the cornerstones of every organization's marketing mix. Product, price, location, and promotion are critical antecedents of purchasing decisions, brand awareness, brand association, brand loyalty, and perceived quality. The present analysis uses four factors that can be summarized as follows. Product refers to online and offline products or services for sale, purchase, or use that fulfill needs or wishes (Kotler & Armstrong, 2012). Product is the basis for all marketing, such as mixing color, design, functionality, quality, and price. Product planning encompasses a range of marketing decisions, including design, technology, usability, value, convenience, price, packaging, branding, and warranties (Singh, 2012). Price is the customer's amount

(Borden & Marshall, 1959) to pay for a product, service, or total value exchanged by consumers to receive or use a product or service (Kotler et al., 2008). The main price factors are product quality evaluation, marketing policy, costs associated with production, advertisement costs, and other market price variability. Price is key to business strategies, serving as a tool to respond to competition and ensuring the company's survival (Sanib et al., 2013). Place includes distribution networks, warehousing facilities, transport mode, and inventory management. It is a system transporting goods and services from service providers and suppliers to customers. Distribution impacts productivity significantly, and the company is supposed to have an outstanding distribution chain and strategic logistics management for any physical or virtual store such as online, wholesale, internet, direct selling, peer-to-peer, or multi-channel location (Singh, 2012). Promotion is the decision to link the product to the target market and have customers purchase it (Lovelock et al., 1998). It is a vital component of the marketing mix and includes promoting corporate marketing strategies through advertising and public relations exhibitions and presentations. Advertising is a dynamic combination of promotional elements to create and improve a company's brand identity, one of the industry's significant competitive advantages that help it retain its solidity. However, the new theory will rename the 4Ps to the 4Cs, representing customer value, cost, convenience, and communication (Rintamäki et al., 2006). The 4Ps focus on the product or service, whereas the 4Cs focus on the consumer, which may be more relevant for digital marketing. Wu and Li (2018) suggest a new marketing mix based on the 6Ss of social commerce: social commerce needs, social commerce risks, social commerce convenience, social capital, social identification, and social influence. All of these factors were weighed in terms of advantages and downsides. Thailand's motorcycle marketing is based on traditional trade, which may make the 4Ps more appropriate to this study.

Brand equity

Brand equity is the sum of the assets and liabilities arising from customer experiences. Several scholars (e.g., Aaker & Keller, 1990; Christodoulides et al., 2015; Keller, 1993) consider brand equity as one of the leading corporate properties that can help explain marketing strategies, mechanisms, and effects (Reynolds & Phillips, 2005). There is three brand equity (Farjam & Hongy, 2015). First, financial brand equity measures a brand's asset value (Simon & Sullivan, 1993). Second, customer-based brand equity tests a customer's response to a brand name (Keller, 1993). Third, employee-based brand equity (Kwon, 2013) is similar to customer-based brand equity but focuses on employee-based employment and the corporate culture environment (King & Grace, 2009). This study applies to customer-based brand equity and its contribution to the product's value-added brand name (Gil et al., 2007). Brand equity elements can be measured as a set of marketing efficiency metrics (Ambler, 2003), adding value to the company's products or services through five components or assets: brand awareness, brand association, perceived quality, brand loyalty, and other proprietary properties (Aaker, 1991). The first four elements are intangible properties, while other proprietary brand properties are more observable brand indicators. Thus, it is not commensurate with the other four components, so almost all researchers use the first four dimensions to measure brand equity.

Keller (1993) measures brand equity on dual factors, brand image and brand awareness. However, Pinar et al. (2020) combine brand awareness, perceived quality, brand association, and brand trust with three additional factors to calculate university brand equity: learning environment, dynamic environment, and university reputation. Yoo and Donthu (2001) evaluate it by measuring brand awareness/association, perceived quality, and brand loyalty. Higher-order brand equity constructs involve formative (Yoo & Donthu, 2001) reflection (Schivinski & Dabrowski, 2016). Four brand equity components are described below.

Brand awareness is a measure of a consumer's brand node strength, meaning how easily a customer can recall and recognize the brand in different situations and circumstances (Kotler & Keller, 2009). Aaker (2010) states that brand awareness is a consumer's willingness to point to a brand into their product category, which leads to a buying decision (Macdonald & Sharp, 2000).

Brand association refers to how strongly a customer feels towards a brand relative to a current consumer experience involving less familiar brand associations. The brand association theory suggests that a business should position itself so that consumers find it attractive and believe that no other product on the market will satisfy their needs. Brand positioning creates a special place in the consumer's minds for a brand giving it a competitive advantage; i.e., the company's products have a strong and significant presence in the consumer's heart and mind.

Brand loyalty is significant brand equity (Aaker, 1991) which defines a customer's probability of moving to another brand should the price or product characteristics be changed. On the one hand, brand loyalty tends to make customers loyal to a focal brand as a first choice (Yoo & Donthu, 2001). It makes a positive contribution to purchasing decisions. Customers will pay a premium for a preferred brand if they believe it is more valuable. The additional expense to customers is justified by brand loyalty. As a result, brand loyalty is critical to the profitability and viability of a business (Chaudhuri & Holbrook, 2001). Due to the increasing unpredictability of the market and the diminishing originality of products, marketers are concentrating their efforts on sustaining and expanding brand loyalty. No prior research has demonstrated a link between brand loyalty and customer-based brand equity. Keller takes a contrary position to Aaker about the significance of brand equity, believing it is a product of it (Keller, 1993; Lei & Chu, 2015).

Perceived quality is the key brand equity element (Aaker, 1991), not actual product quality. It is a subjective consumer value evaluation (Zeithaml, 1988), acknowledging its function in generating a competitive advantage. Perceived quality recognizes a consumer's perception of a fair price for a good or service compared to the competition but has no technological dimension. Generally, a high-quality product/service results in improved consumer satisfaction (Zeithaml, 2000), which may affect quality perception (Dabholkar, 1995). Processing the components of a product affects how customers estimate its quality, resulting in perceived quality (Lindquist & Sirgy, 2003) that incorporates profit (Schroff, 2003). The "perceived quality" approach assesses the perceived quality of a product from the consumer's point of view (Northen, 2000). As part of brand loyalty, perceived quality can affect purchasing decisions (Zeithaml et al., 1996), leading directly to customer loyalty and profitability (Kotler, 2000). The marketing mix and brand equity hypothesis can be created as follows;

H1: The marketing mix is positively related to brand equity.

Purchase decisions

Consumers make purchases and select information based on knowledge of various products, brands, and experiences (Jiang & Rosenbloom, 2005). Purchase decisions can be tracked through several variables, including product quality and price level (Shekhar & Raveendran, 2013), but mainly through brand awareness (Macdonald & Sharp, 2000; Moisescu, 2009), brand association (Ashraf et al., 2018), brand loyalty (Aaker, 1991) and perceived quality (Lee et al., 2019; Zeithaml et al., 1996). Consumer purchase decisions also are affected by the product (Chaudhuri & Ligas, 2009), position (Kotler & Keller, 2009), price, and promotion (Kotler & Armstrong, 2012). The following hypotheses about brand equity and purchase decisions, as well as marketing mix and purchasing decisions, can be developed:

H2. Brand equity is positively related to purchasing decisions

H3. The marketing mix is positively related to purchasing decisions

Hierarchical component model

The HCM can increase content-specific constructs (Becker et al., 2012), and statistical power, achieve parsimonious model status (Polites et al., 2012), and reduce the colinear formative indicators (Hair et al., 2017). The HCM building system has four approaches and four types. The approaches are repeated indicators (Wold, 1982), two-stage (Ringle et al., 2012), hybrid (Wilson & Henseler, 2007), and three-stage (van Riel et al., 2017). The types are reflective-reflective, reflective-formative, formative-reflective, and formative-formative (Ringle et al., 2012). Repeated indicators use repeated indicators in both lower and higher-order constructs. The two-stage approach uses a repeated first-stage indicator approach (Henseler et al., 2007), achieving standard construct scores as higher-order indicators. The hybrid method divides two-part indicators into a lower and higher design for each 50% (van Riel et al., 2017), which may be ambiguous for an odd number of indicators (Cheah et al., 2019). The three-stage approach is no longer feasible (Cheah et al., 2019). Repeated indicators and two-stage methods yield inconsistent results and ignore model fit testing (van Riel et al., 2017), which can be predicted using repeated indicator approaches to discriminant violation (Sarstedt et al., 2019). The repeated indicators approach has three main disadvantages (Cheah et al., 2019). First, the residuals are artificially correlated and must be predicted. Second, an efficient estimation can be obtained, in which a lower-order construct (LOC) has a similar number of indicators. Violating this law would be a biased estimation dependent on the higher-order construct's weights (HOC) (Becker et al., 2012). Third, using reflective-formative HCM as an endogenous construct can clarify almost any variation of HOC, resulting in an R^2 of the LOCs equal to 1.0. Therefore, the researcher would be wrong to conclude that the HOC has no predictors based on the path coefficient results (Ringle et al., 2012). Inline, Hair et al. (2013) suggest using the two-stage approach due to various technical shortcomings of the repeated indicator approaches. The reflective model is determined from the set of measurable effects in the two-stage method drawback, while the formative model is extracted from the collection of latent variables (Fornell & Bookstein, 1982). The second approach, the two-stage method, measures the set of construct variables. Consequently, when assessing stage one construct scores (Wilson & Henseler, 2007), some confounding interpretation occurs (Burt, 1976). The formative need to employ repeated indicators is unacceptable in the second stage. According to Diamantopoulos and Winklhofer (2001), the formative in higher-order models would be beneficial. Bias also exists when a repeated indicator measures a higher-order model (Becker et al., 2012; Hair et al., 2017). The HCM type is commonly used for the reflective-reflective and reflective-formative types (Cheah et al., 2019). Reviewing the past thirty years (1989-2018), Sarstedt et al. (2019) found 57 higher-order PLS-SEM studies, some of which used reflective-reflective, reflective-formative, and both in 7, 8, and 1 review, respectively. 13 reviews used a two-stage approach, while three studies used a repeated indicators approach. The prominent literature approach of HCM is a two-stage, repeated indicator approach that can be used for formative and reflective purposes (Hair et al., 2017) depending on the higher-order model. Thus, the two-stage approach should use the reflective-formative and formative-formative types. The reflective-reflective and formative-reflective types use repeated indicator approaches. The repeated indicator approach can violate discriminatory validity between LOCS and HOC (Sarstedt et al., 2019). Structural model assumptions may often have a misleading effect if the definition lacks discriminant validity resulting in a measurement model (Farrell & Rudd, 2009). Sarstedt et al. (2019) obtained discriminative validity by manually measuring from it using repeated indicator approaches while lacking a parameter fit model. Becker et al. (2012) propose a disjointed two-stage approach that improves the repeated indicators approach at the first stage without a higher-order component. Hair et al. (2017) note that Baker et al.'s two-stage approach can measure both the first and second stages as reflective or formative. The first stage will assess how well indicators organize their constructs, while the second stage will examine the relationships between constructs. As a result, the lower-order construct will present a measurement model, while the higher-order construct will display a structural model. That would be ideal if both levels could show the model fit index.

Consistent partial least square and composite model

There are three types of models: reflective, causal-formative, and composite measurement. They may be classified depending on the construct's nature, i.e., a systemic or behavioral investigation mechanism. Behavioral science models typically have latent variables, generally built through reflective estimates. A common factor involving a new manifestation of minus measurement errors is the variables (Kock, 2015). That is the principal source of mode A's estimated bias parameter (Antonakis et al., 2010). Although the sample size is infinite, bias still exists (Kock, 2017). Therefore, some scholars have abandoned the use of mode A (Rönkkö et al., 2015), especially in the field of research in psychology (Rönkkö & Everman, 2013). Dijkstra and Henseler (2015a & b) propose that PLSc can solve the mode A problem. In PLSc, the indicators are determined by a common factor (Schuberth et al., 2018) or latent variable. Kock (2017) notes that PLSc was a bias-corrected parameter that could produce statistical power lower than other methods.

Indicators are an antecedent that uses the causal-formative measurement for the construct component using the mode B algorithm. Like multiple regression, the causal-formative relationship makes measurement errors in the constructed variables. Multicollinear relationships should not exist between indicators and are not interchangeable if any indicators are omitted, resulting in increased measurement errors. Many scholars (e.g., Aguirre-Urreta et al., 2016) find a single causal-formative indicator challenging to exclude. That will have an impact on the essential characteristics of the constructed variables. More than that, all indicators follow one definition (Bainter & Bollen, 2015), each left to the confounding interpretation that refers to the nominal and empirical difference in meaning, which would change the importance of the construct (Henseler et al., 2015). Most scholars consider a casual-formative deficit a bias (e.g., Rönkkö et al., 2016); thus, Rigdon (2016) suggests abandoning it. As represented for all models, MIMIC needs to use causal-formative (Benitez, et al., 2020; Henseler, 2017).

Design constructs define their composites as indicator mixtures (Henseler, 2017), and measurements of weighted composites as linear indicator combinations (Kock, 2017). In causal-formative models, scientists may use composite models to measure the constructed variable in which the artifact or design-construction is used (Schuberth et al., 2018). Composite measurement has a few overall disadvantages, with the main downside being that the amount of inter-constructed correlations and the respective indicator loads between indicators refer to all correlations (Henseler, 2017). Nevertheless, the composite measurement model requires no assumptions about the relationships between its indicators; they may have any value. As a result, the correlations between indicators will need to be of better quality. The application of internal consistency to composite measurement models is of little interest to measure things concerning their nomological network. The constructions described as composites usually require an embedded context (Henseler, 2017).

The quality of PLS-SEM

The quality of PLS-SEM should be considered from the model fit index, measurement, and structural model. In model fit criteria, the saturation model determines the goodness of model fit. The model used was bootstrapped to detect the data's inconsistency and the model-inferred correlation matrix (Dijkstra & Henseler, 2017). There are three statistics to consider: standardized root means square residual (SRMS), unweighted minimum square discrepancy (d_{ULS}), and geodesic discrepancy(d_G). First, there are two requirements, considering the bootstrapping results of 95% (HI95) and 99% (HI99), that should be lower than the specifications. Second, the SRMR value should be below 0.08 (Hu & Bentler, 1999), to consider whether the first condition can or cannot be met.

Reflective measurement model parameters have internal consistency, indicator reliability, convergent validity, and discriminative validity. Internal consistency and test accuracy indicate that the questionnaire can measure the same things. Dijkstra-Henseler's rho (ρ_A), Jöreskog's rho (ρ_C) and Cronbach's alpha are expected to weigh more than 0.70. The indicator's reliability should surpass 0.708 (Henseler et al., 2015), indicating that the indicator can determine its construct. It may explain more than 50% of the indicator variance, rendering the item fairly reliable (Henseler et al., 2015). Convergent validity and discrimination test the technical characteristics or behavior. The convergence thumb law is that the average extracted variance (AVE) in the construct score should surpass 0.50 to indicate an indicator variance (Hair et al., 2017). Using Hetrotrait Monotrait correlations (HTMT), the discriminating validity test should be distinct, below 0.85 (Henseler et al., 2015).

The composite measurement criteria may be the same as the formative (Hair et al., 2020). They are nomological network, multicollinearity, the significance of loading, weight, and loading relevance (Henseler, 2017). Nomological validity, the determination of the formative indicator, meets the assumptions, including the specific component construction indicator. Multicollinear inflation factor variance (VIF) estimates should not exceed 5 (Hair et al., 2011). Weight is expected to be significant, but if it is negligible, the load must be substantial and not less than 0.50, which will keep the indicator inside the model.

The structural model will consider the R-square (R^2), effect size (f^2), predictability (Q^2), and path coefficient. In social science studies, R^2 is divided into three dimensions, representing low, moderate, and adequate 0.25, 0.35, and 0.75 respectively (Hair et al., 2010), and is estimated to exceed medium size (Chin, 1998). Divide effect sizes are 0.02, 0.15, and 0.35 for small, medium, and significant, respectively (Cohen, 1988), and should be medium at least. The path coefficient is significant though Q^2 is unavailable in ADANCO.

Conceptual framework

This study is a continuation of Jhantasana (2019), which used PLSc to explore the influence of brand loyalty and brand awareness on motorbike purchase choices. The marketing mix and brand equity were considered in this study as composite variables. The brand equity and the marketing mix are second-order constructs that use a disjointed two-state approach and a formative-formative weighting scheme in a composite model. Purchasing decision is a latent variable or PLSc model. The conceptual framework of this analysis is depicted in Figure 1.

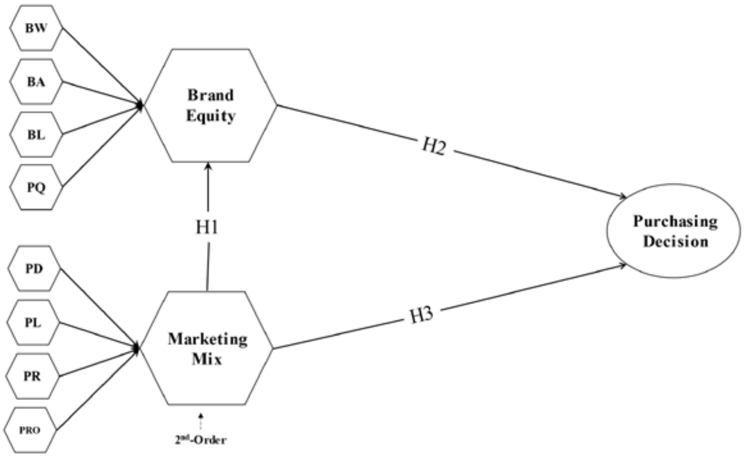

Figure 1 Conceptual framework

Methodology

Population and sample

The number of registered motorcycle users is 21.40 million units in Thailand (Department of Land Transport, 2019). Sopar (2019) analyzed sample size using an effect size, statistical power, number of latent variables, number of indicators, and probability level equivalent to 0.15, 0.80, 9, 34, and 0.05, respectively. According to the Sopar (2019) method, the sample size model structure sets a minimum sample size of 114. Power and alpha are typical values, while latent variables are models. Hair et al. (2017) note that the path coefficient might be significant if the effect size reaches the mean (0.15) in a small sample analysis. In January 2019, a questionnaire was sent to a group of around 200 bike riders in Pakchong district, Nakhonratchasima province, utilizing a conventional approach that collected 130 samples, as shown in Jhantasana (2019). Thus, this research gathered additional data from 18 identical questionnaires to determine the study's minimal sample size in Pathum Thani province in September 2019.

Questionnaires

Table 1 shows the questionnaire comprised of 34 indicators and 9 constructs. The marketing mix includes product, price, place, and promotion. Customer-based brand equity comprises brand awareness, perceived quality, brand association, and brand loyalty. Another construct is the purchase decision. The questionnaire was adapted from Distlek (2017) and was reviewed using a 5-point Likert scale ranging from "strongly accepted" to "strongly disagree". Cronbach's Alpha value for each construct range between 0.845 and 0.906.

Table 1 Questionnaire to determine the motorcycle brand purchased

Items	
Product (Cronbach's Alpha,0.845)	
PRD1	Brand X is modern and beautiful.
PRD2	Brand X has several models.
PRD3	Brand X's performance is high and highly reliable.
PRD4	Brand X uses ABS brakes on most of its models.
PRD5	Brand X is fuel efficient.
Price (Cronbach's Alpha,0.906)	
PRI1	Brand x's prices are fair.
PRI2	There are many payment options available when buying brand X.
PRI3	The price of spare parts is fair for brand X.
PRI4	Down payments, interest rates, and payment periods are fair.
Place (Cronbach's Alpha,0.902)	
PLA1	The location of stores is very convenient for traveling.
PLA2	There are several after-sale support centers.
PLA3	There are several service channels for each store.
PLA4	Each shop has a customer service area.
Promotion (Cronbach's Alpha,0.890)	
PRO1	Brand X has many advertising channels, such as newspapers, TV, and websites.
PRO2	Brand X has been shown at many events like the Motor Show.
PRO3	Brand X displays the prices clearly in every store.
PRO4	Brand X promotes fair prices.
Brand awareness (Cronbach's Alpha,0.848)	
BW1	X brand can be found in multi-channel ads.
BW2	X brand can be recalled quickly.
BW3	Brand X is easily recognized.
Perceived quality (Cronbach's Alpha,0.880)	
PQ1	Brand X's design is higher than that of other brands.
PQ2	Brand X suits people better than other brands.
PQ3	Brand X's overall quality is higher than that of other brands.
Brand association (Cronbach's Alpha,0.891)	
BA1	Brand X mirrors the customer image.
BA2	Brand X reflects customer lifestyle.
BA3	Brand X reflects customer taste.
Brand loyalty (Cronbach's Alpha,0.909)	
BL1	When buying a motorcycle, buy brand X.
BL2	Recommend brand X to others.
BL3	Buy brand X, even if other brands are offering promotions.
Purchase decision (Cronbach's Alpha,0.894)	
PD1	Compare the price, quality, and model of several brands.
PD2	Friends of the customer or sellers recommend brand X.
PD3	The customer likes the quality of brand X.
PD4	The customer's experienced with brand X is good.
PD5	The customer can easily find real products or advertisements of the brand X

Estimating

Marketing mix and brand equity are hierarchical components of a disjointed two-stage approach (Becker et al., 2012) and formative-formative types for composite models. The relationship between the marketing mix item, the brand equity aspect, and the purchasing decision can be studied using the improved repeat indicator approach (Becker et al., 2012). The purchasing decision construct is a first-order construct using a reflective model. This work will analyze both first- and second-order relationships—all estimates will be done using ADANCO bootstrapping 4,999 rounds (Henseler & Disjkatra, 2017).

Results

Information on sample data

The results reveal that most individuals in the sample were male, approximately 84%, aged 25 to 34 and 35 to 49 (64.7% and 25.3%, respectively). About 42% not have bachelor's degrees while 54.7% did. They worked in government/state-owned companies, private firms, and small business owners 19.3%, 51.3%, and 18.7%, respectively, with earning below 10,000 or 10,001-20,000 baths per month, 39.3% and 37.7%, respectively. Honda and Yamaha's motorcycles accounted for 36.7% and 25.3% of the survey, respectively.

First-order construct

Test of model fit

Table 2 shows that for the saturated model, SRMR and d_{ULS} are below the bootstrapping results of 95% (HI95), while d_G is below the bootstrapping results of 99% (HI99). SRMR is also lower than 0.080. The three values of model fit indexes had no fit at the start of the measurement. Some indicators must be removed from both the emergence and latent variable models. The bias indicators PRD1, PRD3, PRD4, PRI1, PRO2, and PRO3 with shallow values and a negative sign can be removed from the emergence variable model. After the largest multicollinear to PLA3, the PLA4 would be removed. PD4 was removed from the latent variable model when the loading was less than 0.708. Consequently, the model fit index improves to statistical significance, as seen below.

Table 2 Overall model fit index

Discrepancy	Overall Saturate Model Fit Evaluation			
	Value	HI95	HI99	Conclusion
SRMR	0.046	0.051	0.057	Supported
d_{ULS}	0.691	0.836	1.059	Supported
d_G	0.678	0.623	0.715	Supported

The measurement models

The emergence variables are measured using composite model criteria, while the latent variables, or PLSc, are measured using reflective criteria. In the composite model, since all of the network's interactions are provided in a single model evaluation, nomological validity is validated, as seen in Table 3. (Hagger et al., 2017). When considering the t-statistic of weight, specific indicators, include PRD2, PRI2, PRI3, PLA1, PQ2, BA3, BL1, and BL3, seem insignificant. However, since their loading is more significant than 0.50, they will continue in the model. All indicators have no multicollinearity since all VIF values are below 5. In the PLSc model, the internal consistency showed by Dijkstra-Henseler's rho, Jöreskog's rho, and Cronbach's alpha, is higher than 0.70. The results for loading display reliability indicators that are higher than 0.708. The AVE is 0.620, indicating the convergence validity.

Second-order construct

In most cases, the first-order model can only be reported as a measurement model, while the second-order model should be reported as a structural model. On the other hand, this research documented second-order model fit indexes, measurements, and structural models to show the quality of the composite model. It is particularly able to generate model fit indices at both stages.

Test of model fit

Table 4 shows that the model fit parameters for the composite model value of the saturated model are the same as for the estimated model. SRMR, and d_{ULS} are below the bootstrapping results of 95% (HI95), while d_G is slightly higher than HI95 but lower than HI99. Thus, all of the hypotheses for the model fit test were supported.

Table 3 Measurement model criteria of emergent and latent variable

Emergent variables	Weighting	Loading	t-Weighting	VIF
Product				
PRD2	0.228	0.634	0.975	1.276
PRD5	0.873	0.979	5.459	1.276
Price				
PRI2	0.148	0.859	0.812	3.118
PRI3	0.198	0.926	0.793	4.886
PRI4	0.698	0.988	3.279	4.629
Place				
PLA1	0.142	0.716	0.750	1.688
PLA2	0.481	0.929	2.233	2.475
PLA3	0.483	0.936	1.966	2.672
Promotion				
PRO1	0.477	0.856	3.345	1.539
PRO4	0.641	0.923	4.781	1.539

Emergent variables	Weighting	Loading	t-Weighting	VIF
Brand awareness				
BW1	0.195	0.701	1.444	1.508
BW2	0.551	0.960	2.206	3.423
BW3	0.360	0.929	1.524	3.448
Perceived quality				
PQ2	0.306	0.906	1.377	3.013
PQ3	0.734	0.984	3.546	3.013
Brand association				
BA1	0.525	0.912	4.323	1.919
BA2	0.498	0.918	3.375	4.385
BA3	0.075	0.853	0.463	4.198
Brand loyalty				
BL1	0.173	0.840	0.699	2.696
BL2	0.584	0.965	1.425	3.142
BL3	0.315	0.925	0.654	3.813

Latent variable	Load ing	Dijkstra-Henseler's rho (ρ_A)	Jöreskog's rho (ρ_c)	Cronbach's alpha(α)	The average variance extracted (AVE)
Purchasing decision		0.867	0.867	0.867	0.620
PD1	0.781				
PD2	0.775				
PD3	0.780				
PD5	0.812				

Table 4 Test of model fit

Discrepancy	Overall Saturate Model Fit Evaluation			
	Value	HI95	HI99	Conclusion
SRMR	0.041	0.044	0.048	Supported
d_{ULS}	0.150	0.177	0.214	Supported
d_G	0.146	0.142	0.178	Supported

Measurement model

In table 5, for the composite model in a single model evaluation, all of the network's connections are given, and nomological validity is confirmed. Almost all marketing mix and brand equity indicators are significant, except for_place and perceived quality, which have loadings greater than 0.50. The VIF of all indicators is less than 5, indicating that there was no multicollinearity. For the PLSc model, the internal consistency values shown by Dijkstra-Henseler's rho and Jöreskog's rho exceed 0.70. The indicator reliability was strong, with all indicators above 0.708. Convergence validity (AVE) was higher than the criteria.

Table 5 Measurement model of second-order construct

Emergent variables		Weighting	Loading	t-Weighting	VIF
Marketing Mix					
Product		0.357	0.715	3.074	1.370
Price		0.339	0.823	2.538	1.897
Place		0.097	0.636	0.841	1.549
Promotion		0.495	0.816	4.704	1.409
Brand Equity					
Brand loyalty		0.598	0.939	5.210	2.516
Brand association		0.285	0.763	2.505	2.118
Brand awareness		0.243	0.877	1.959	2.743
Perceived quality		0.012	0.648	0.100	1.885
Latent Variable	Loading	Dijkstra-Henseler's rho (ρ_A)	Jöreskog's rho (ρ_c)	Cronbach's alpha(α)	The average variance extracted (AVE)
Purchasing decision		0.897	0.894	0.895	0.630
PD1	0.810				
PD2	0.787				
PD3	0.797				
PD4	0.716				
PD5	0.851				

Structural model: Table 6 and Figure 2 revealed that there is significance between marketing mix and brand equity, purchase decision and brand equity, and purchasing decision. Based on t-statistics, the relationship between marketing mix and brand equity was strongest.

Table 6 Path coefficient, effect size, and assumption

Effect	Beta	P-value	t-value	Cohen's f^2	R^2	Hypothesis test
Marketing Mix -> Brand Equity	0.699	0.000	16.293	0.956	0.489	Support
Brand Equity -> Purchasing Decision	0.426	0.000	4.126	0.184	0.495	Support
Marketing Mix -> Purchasing Decision	0.337	0.000	3.500	0.115	0.495	Support

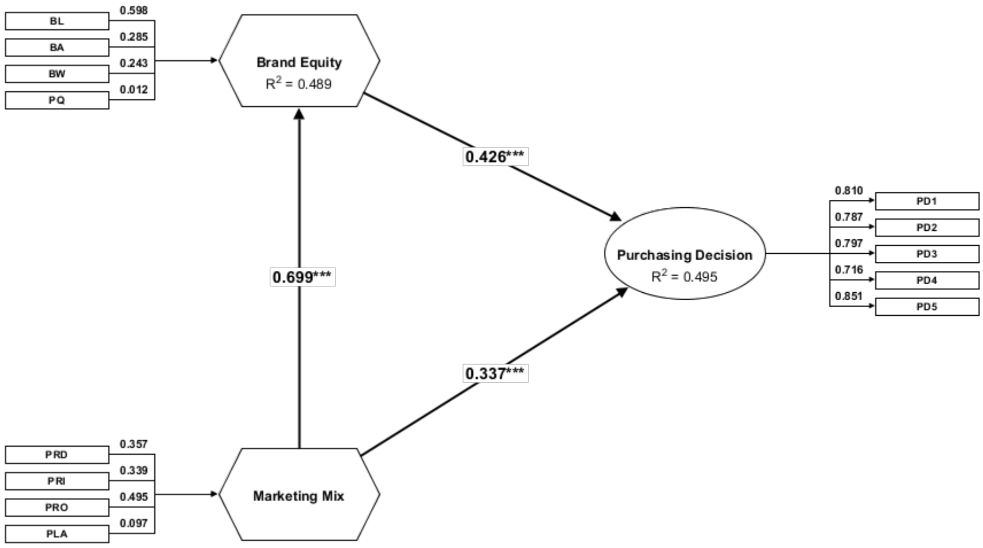

Figure 2 Structural model

Discussion

Summary of research

In this analysis, the composite model is used for marketing mix and brand equity, while PLSc is used for purchasing decisions. The disjointed two-state approach and formative-formative type are used for second-order construct in both emergence variables. Any bias indicators in lower-order constructs must be removed for the overall fit index to improve. In contrast to Sarstedt et al. (2019), the algorithm will generate a total model fit lower-order and higher-order constructs. The application of emergence variables to the marketing mix and brand equity was well established, with all three paths between constructs being significant.

Interpretation and practical implications

For the lower-order construct, this study sought to know whether the marketing mix factor and brand equity element affect a motorcycle's purchasing decision. None of the results had a marketing mix on purchasing decisions that diffed from Satit et al. (2012). They found a significant impact on customer travel agent's production and price decision. For the relationship between the marketing mix dimension and brand equity component, only the price effect on brand awareness and brand loyalty and promotion affected brand awareness and perceived quality. Thus, Thailand's motorcycle prices impacted brand awareness and encouraged customers to buy. That implies a brand with fair motorcycle prices, multiple outlets, reasonable spare part prices, reasonable down payments, flexible interest rates, and payment periods that effectively allow brand awareness-association effects on purchase decisions. Suppose there are several promotional channels or not?, Promoting of brand X bikes can be achieved through several activities, mainly showing price and having fair price promotions that will impact brand awareness-association and perceived quality. Inline, Huang, and Sarigöllü (2012) noticed that price promotion efficiently created brand awareness consumer-packaged products. Aghaei et al. (2014) found positive and substantive relationships between the brand equity dimension and service marketing mix in chain stores. Customers can recall and recognize a motorbike brand, and expect it to express a particular lifestyle and taste. The investigation of the link between the brand equity element and purchasing decision revealed that only brand awareness had an impact on motorcycle buying decisions. The result showed that when consumers consider multi-channel advertising. Motorcycles, can remember and recognize the brand. They expect a brand of bikes to reflect a particular lifestyle and taste. In Thailand, buying is usually based on price, quality, trial use, and advice from friends and sellers. Inline, Moisescu (2009) stated that brand awareness, as one of brand equity's core dimensions, is a prerequisite for consumer purchasing decisions as it is the primary reason to accept a brand. Gunawardane (2015) found that brand awareness and perceived quality privately relate to purchasing intent. Any unclear in lower-order construct relationship arising from the constraints of the 4P marketing mix may no longer be considered a cornerstone of the customer marketing strategy, which consisted of three main things (Constantinides, 2006): First, the lack of consumer orientation, second, the lack of customer contact, and third the lack of strategic elements, which is a significant system deficiency, making it insufficient for planning in an environment where external and uncontrollable variables decide the business's competitive opportunities and challenges. The results showed that marketing mixes are significantly related to purchasing decisions and brand equity for the second-order effect. In contrast, brand equity is related to purchasing decisions, as found by Macdonald and Sharp (2000). The current study shows that using the composite model for marketing mix and brand equity is more effective. Analysts can determine the composite measurement model and establish its credibility compared to explicitly modeling random measurement errors. Therefore, as an artifact, brand equity is critical (Henseler, 2017). Exclude any bias indicators whose quality falls below the latent or emergence variable requirements to improve the overall fit index.

Theoretical Implications

The results suggest that the marketing mix is positively related to production, price, place, and promotion. Nearly all the marketing mix aspect analysis (e.g., Yoo et al., 2000) is insignificant as in the current research. For the higher-order construct, however, the result showed that marketing mix and brand equity are significant to purchasing decisions. The HCM can improve content-specific constructs, statistical power, and parsimonious model status (Polites et al, 2012), and minimize colinear formative indicators (Becker et al., 2012). The second-order construct of a composite model will generate model fit indexes for both stages when used in combination with a disjoined two-stage approach and a formative-formative type.

Limitations and directions for further research

Although, the critical findings of this report can accurately answer particular questions, some drawbacks must be considered. First, a limitation of the current research is that it does not account for the combustion chamber volume of the motorcycle. Customers desire motorcycles of varying sizes, as seen by their purchasing preferences. This variable could be further studied. Second, the 4P marketing mix may need to be revised for today's motorcycle market situation in Thailand. The motorcycle market was partially traditional at the time of the study, with a mix of onsite and online or e-commerce transactions. Additionally, the researcher may need to investigate additional marketing mix elements, such as the 4Cs or 6Ss, or select an indication to combine with the 4Ps that is appropriate for the contents of the study. This study, however, supports O'Connor and Galvin's (1997) findings, which state that the new product combination can be studied, but the first 4Ps must remain the cornerstone. On the other hand, Wichmann et al. (2021), characterize the marketing mix's evolution in terms of four essential questions: who is involved in the marketing mix, what does the marketing mix entail, how is it implemented, and where is it deployed? A third weakness is that, more brand equity aspects should be developed to reduce confusion that brand loyalty is a dimension or output of brand equity (Aaker, 1991; Juntunen et al., 2010).

Conclusion

Thus, research studies the brand equity and marketing mix related to buying motorcycles in Thailand using the PLS-SEM hierarchical component model. This study found that some bias indicators must be removed from the composite and PLSc models, resulting in the hypothesis of three model fit indexes being accepted. In the higher-order construct, the marketing mix is essential in purchase decisions and brand equity, with brand equity being signed to purchase decisions. In this case, the composite model is more suitable when applying the artifact's brand equity and marketing mix. Although incorporating composite or emergent factors with behavior or attitude variables is a relatively new concept, it is feasible to aid future researchers (Hubona et al., 2021; Jhantasana, 2022). Additionally, this study benefits stakeholders in the motorcycle business who may be interested in the finding that marketing plans should encompass more than the four Ps.

References

Aaker, D. A. (1991). *Managing brand equity: Capitalizing on the value of a brand name.* New York: Free Press.

Aaker, D. A. (2004). *Brand portfolio strategy: Creating relevance, differentiation, energy, leverage, and clarity.* New York: Free Press.

Aaker, D. A. (2010). *Building strong brands.* London, UK: Simon & Schuster.

Aaker, D. A., & Keller, K. L. (1990). Consumer Evaluations of Brand Extensions. *Journal of Marketing*. 54(1), 27-41.

Aghaei, M., Vahedi, E., Kahreh, M. S., & Pirooz, M. (2014). An examination of the relationship Between the services marketing mix and brand equity dimensions. *Procedia-Social and Behavioral Sciences.* 109, 865-869.

Aguirre-Urreta, M. I., Rönkkö, M., & Marakas, G. M. (2016). Omission of causal indicators: consequences and implications for measurement. *Measurement: Interdisciplinary Research and Perspectives.* 14(3), 75-97.

Al Badi, K. S. (2018). The impact of marketing mix on the competitive advantage of the SME sector in the Al Buraimi Governorate in Oman. *SAGE Open*, *8*(3), 2158244018800838

Ambler, T. (2003). *Marketing and the bottom line: The marketing metrics to pump up cash flow*. London, Great Britain: Prentice-Hall.

Antonakis, J., Bendahan, S., Jacquart, P., & Lalive, R. (2010). On making causal claims: A review and recommendations. *The Leadership Quarterly*, *21*(6), 1086-1120.

Ashraf, M., Sulehri, H. A., & Abbas, S. (2018). Impact of brand association on consumer buying behavior in foot ware industry: The case of Punjab, Pakistan. *International Journal of Academic Research in Business and Social Sciences, 8*(3), 91-102.

Bainter, S. A., & Bollen, K. A. (2015). Moving forward in the debate on causal indicators: rejoinder to comments. *Measurement: Interdisciplinary Research & Perspectives, 13*(1), 63-74.

Baron, S., & Jones, P. (Eds.). (1991). *Macmillan dictionary of retailing.* London, UK: Macmillan International Higher Education.

Baumgartner, J. 1991. Nonmarketing Professionals Need More than 4Ps. *Marketing News* 22 July, 28.

Becker, J. M., Klein, K., & Wetzels, M. (2012). Hierarchical latent variable models in PLS-SEM: Guidelines for using reflective-formative type models. *Long Range Planning, 45*(5-6), 359-394.

Benitez, J., Henseler, J., Castillo, A., & Schuberth, F. (2020). How to perform and report an impactful analysis using partial least squares: Guidelines for confirmatory and explanatory IS research. *Information & Management, 57*(2), 103-168.

Booms, B. H., & Bitner, B. J. (1980). *Marketing strategies and organization structures for service firms* (pp. 47-51). In Donnelly, J., & George, W. R. (Eds.). Marketing of services. Chicago, USA: American Marketing Association.

Borden, N. H. (1964). The concept of the marketing mix. *Classic*, *2*, 7-12.

Borden, N. H., & Marshall, M. V. (1959). *Advertising management: Text and cases.* Homewood, USA: Richard D. Irwin.

Burt, R. S. (1976). Interpretational confounding of unobserved variables in structural equation models. *Sociological Methods and Research, 5*, 3-52.

Chaudhuri, A., & Ligas, M. (2009). Consequences of value in retail markets. *Journal of Retailing, 85*(3), 406-419.

Cheah, J. H., Ting, H., Ramayah, T., Memon, M. A., Cham, T. H., & Ciavolino, E. (2019). A comparison of five reflective–formative estimation approaches: Reconsideration and recommendations for tourism research. *Quality & Quantity, 53*(3), 1421-1458.

Chin, W. W. (1998). *The partial least squares approach to structural equation modeling* (pp. 295-336). In Marcoulides, G. A. (Ed.). Modern methods for business research. New Jersey: Lawrence Erlbaum Associates

Christodoulides, G., Cadogan, J. & Veloutsou, V. (2015). Consumer-based brand equity measurement: lessons learned from an international study, *International Marketing Review, 32*(3-4), 307-328.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences*. New York, USA: Academic Press.

Constantinides, E. (2002). The 4S web-marketing mix model, electronic commerce research, and applications. *Elsevier Science*, *1*(1), 57-76.

Constantinides, E. (2006). The marketing mix revisited: Towards the 21st century marketing. *Journal of Marketing Managemen*, *22*(3-4), 407-438.

Culliton, J. W. (1948). *The management of marketing costs.* Boston, USA: Division of Research, Graduate School of Business Administration. Harvard University, Boston, *MA*, 400-420.

Czinkota, M. R. (2000). International information cross-fertilization in the marketing-an empirical assessment. *European Journal of Marketing*, *34*(11/12), 1305-1314.

Department of Land Transport. (2019, January 15). *The number of vehicles registered in Thailand as of 31 December 2019*. Retrieved from https://web.dlt.go.th/statistics/

Diamantopoulos, A., & Winklhofer, H. M. (2001). Index construction with formative indicators: An alternative to scaling development. *Journal of Marketing Research, 38*(2), 269-277.

Dijkstra, T. K., & Henseler, J. (2015a). Consistent and asymptotically normal PLS estimators for linear structural equations. *Computational Statistics & Data Analysis, 81*(1), 10-23.

Dijkstra, T. K., & Henseler, J. (2015b). Consistent partial least squares path modeling. *MIS Quarterly, 39*(2), 297-316.

Dijkstra, T. K., & Schermelleh-Engel, K. (2014). Consistent partial least squares for nonlinear structural equation models. *Psychometrika*, *79*(4), 585-604.

Distlek, K. (2017). *The decision to buy a motorcycle big-bike in Nonthaburi province* (Master's thesis). Pathum Thani, Thailand: Bangkok university, BU Research.

Eavani, F., & Nazari, K. (2012). Marketing mix: A critical review of the concept. *Elixir International Journal*, *49*, 9914-9920.

Falk, R. F., & Miller, N. B. (1992). *A Primer for soft modeling*. Ohio, USA:University of Akron Press.

Farjam, S., & Hongyi, X. (2015). Reviewing the concept of brand equity and evaluating consumer-based brand equity (CBBE) models. *International Journal of Management Science and Business Administration*, *1*(8), 14-29.

Farquhar, P. H. (1989). Managing brand equity. *Marketing Research, 1*(3), 24-33.

Farrell, A. M., & Rudd, J. M. (2009). *Factor analysis and discriminant validity: A brief review of some practical issues*. In D. Tojib (Ed.), ANZMAC 2009 Conference Proceedings (pp. 217-223). ANZMAC.

Fornell, C., & Bookstein, F. L. (1982). Two structural equation models: LISREL and PLS applied to consumer exit-voice theory. *Journal of Marketing Research*, *19,* 440-452.

Frey, A. W. (1961). *Advertising.* (3rd eds.). New York: The Ronald Press.

Gil, R. B., Anders, E. F., & Salinas, E. M. (2007). Family as a source of consumer-based brand equity. *Journal of Product & Brand Management, 16*(3), 188-199.

Goldsmith, R. E. (1999). The Personalised Marketplace: Beyond the 4Ps. *Marketing Intelligence and Planning, 17*(4), 178-185.

Gronroos, C. (1994). From marketing mix to relationship marketing: Towards a paradigm shift in marketing. *Asia-Australia Marketing Journal*, *2*(1), 9-29.

Gunawardane, N. R. (2015). Impact of brand equity towards purchasing decision: A situation on mobile telecommunication services of Sri Lanka. *Journal of Marketing Management, 3*(1), 100-117.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate data analysis.* (7th eds.). New York, USA: Upper Saddle River, NJ: Prentice-Hall.

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., & Thiele, K. O. (2017). Mirror, mirror on the wall: A comparative evaluation of composite-based structural equation modeling Methods. *Journal of the Academy of Marketing Science, 45*(5), 616-632.

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing Theory and Practice, 19*(2),139-151.

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2013). Partial least squares structural equation modeling: Rigorous applications, better results, and higher acceptance. *Long Range Planning*, *46*(1-2), 1-12.

Hair, J. F., Sarstedt, M., Ringle, C. M., & Gudergan, S. P. (2017). *Advanced issues in partial least squares structural equation modeling.* London, UK: Sage publications.

Hair, J.F. Howard, M.C., Nitzl, C. (2020). Assessing measurement model quality in PLS-SEM using confirmatory composite analysis. *Journal of Business Research, 109,*101-110.

Henseler, J. & Dijkstra, K. (2017). ADANCO 2.0. 1. *In 9th international conference on PLS and related methods. PLS 2017*.

Henseler, J. (2017). Bridging design and behavioral research with variance-based structural equation modeling. *Journal of Advertising, 46*(1), 178-192.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*(1), 115-135.

Henseler, J., Wilson, B., Gotz, O., & Hautvast, C. (2007). Investigating the moderating role of fit on sports sponsorship and brand equity. *International Journal of Sports Marketing and Sponsorship, 8*(4), 321-329.

Howell, R. D. (2014). What is the latent variable in causal indicator models? *Measurement: Interdisciplinary Research & Perspectives, 12*(4), 141-145. http://dspace.bu.ac.th/ browse?type=author&value=กรชนก+ดิษฐเล็ก&value_lang=th

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural equation modeling: a Multidisciplinary Journal, 6*(1), 1-55.

Huang, R., & Sarigöllü, E. (2012). How brand awareness relates to market outcome, brand equity, and the marketing mix. *Journal of Business Research, 65*(1), 92-99.

Jalilvand, M. R., Samiei, N., & Mahdavinia, S. H. (2011). The effect of brand equity components on purchase intention: An application of Aaker's model in the automobile industry. *International Business and Management, 2*(2), 149-158.

Jhantasana. C. (2019). Path analysis of brand loyalty and awareness of purchasing decision of motorcycles using consistent partial least square. *Veridian E-Journal Silpakorn University, 12*(6), 1883-1904.

Jiang, P., & Rosenbloom, B. (2005). Customer intention to return online: Price perception, attribute-level performance, and satisfaction unfolding over time. European Journal of Marketing, *39*(1/2), 150-174.

Jobber, D. (2001). *Principles and practice of marketing.* (3rd eds.). England: McGraw-Hill.

Judd, V. C. (1987). Differentiate with the 5th P: People. *Industrial Marketing Management, 16*(4), 241-247.

Juntunen, J., Juntunen, M., & Juga, J. (2010). Corporate brand equity and loyalty in B2B markets: A study among logistics service purchasers. *Brand Management, 18*(4/5), 300-311.

Kapferer, J. N. (2008). *The new strategic brand management: Creating and sustaining brand equity long term.* (4th eds.). London: Kogan Page Publishers.

Keller, K. L. (1993). Conceptualizing, measuring, and managing customer-based brand equity. *Journal of Marketing, 57*(1), 1-22.

Kim, A. J., & Ko, E. (2012). Do social media marketing activities enhance customer equity? An empirical study of luxury fashion brand. *Journal of Business Research, 65*(10), 1480-1486.

King, C., & Grace, D. (2009). Employee based brand equity: A third perspective. *Services Marketing Quarterly, 30*(2), 122-147.

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of e-Collaboration, 11*(4): 1-10.

Kock, N. (2017). Which is the best way to measure job performance: self-perceptions or official supervisor evaluations? *International Journal of e-Collaboration, 13*(2), 1-9.

Kock, N. (2019). Factor-based structural equation modeling with WarpPLS. *Australasian Marketing Journal, 27*(1), 57-63.

Kotler, P. (1986). *Principles of marketing.* (3rd eds.). New Jersey: Prentice-Hall.

Kotler, P. (2000). *Marketing management.* (10th eds.). New Jersey: Prentice-Hall.

Kotler, P., & Armstrong, G. (2012). *Principles of marketing.* (14th eds.). England: Pearson Education Limited, Essex.

Kotler, P., & Keller, K. (2009). *Marketing management.* (13th eds.). N.J.: Pearson Prentice-Hall.

Kotler, P., Armstrong, G., Wong, V., & Saunders, J. (2008). *Principles of marketing.* London: Prentice-Hall.

Kwon, Y. (2013). *The Influence of employee-based brand equity on the health supportive environment and culture–organizational citizenship behavior relation* (Doctoral dissertations). Michigan, USA: University of Michigan.

Lazer, W., Culley, J. D., & Staudt, T. (1973). *The concept of the marketing mix* (pp. 39-43) In Britt, S. H. (Ed.). Marketing manager’s handbook. Chicago: The Dartnell Corporation.

Lee, J. E., Goh, M. L., & Noor, M. N. (2019). Understanding the purchase intention of university students towards skincare products. *PSU Research Review, 3*(3), 161-178.

Lovelock, C. H., Patterson, P. G., & Walker, R. H. (1998). *Services marketing, Australia, and New Zealand.* Sydney: Prentice-Hall.

Macdonald, E. K., & Sharp, B. M. (2000). Brand awareness effects on consumer decision making for a common, repeat purchase product: A replication. *Journal of Business Research, 48*(1), 5-15.

MaGrath, A. J. (1986). When marketing services, 4Ps are not enough. *Business Horizons, 29*(3), 45-50.

McCarthy, E. J. (1964). *Basic marketing: A managerial approach.* Illinoi, USA: Richard D. Irwin.

Moisescu, O. I. (2009). The importance of brand awareness in consumers’ buying decisions and perceived risk assessment. *Management & Marketing-Craiova, 1*, 103-110.

O’Connor, J., & Galvin, E. (1997). *Marketing and information technology the strategy, application, and implementation of IT in marketing.* London: Pitman Publishing.

Pinar, M., Girard, T., & Basfirinci, C. (2020). Examining the relationship between brand equity dimensions and university brand equity: An empirical study in Turkey. *International Journal of Educational Management, 34* (7), 1119-1141.

Polites, G. L., Roberts, N., & Thatcher, J. (2012). Conceptualizing models using multidimensional constructs: A review and guidelines for their use. *European Journal of Information Systems, 21*(1), 22-48.

Rafiq, M., & Ahmed, P. K. (1995). Using the 7Ps as a generic marketing mix: An exploratory survey of UK and European marketing academics. *Marketing Intelligence & Planning, 13*(9), 4-15.

Reinartz, W., Krafft, M., & Hoyer, W. D. (2004). The customer relationship management process: Its measurement and impact on performance. *Journal of Marketing Research, 41*(3), 293-305.

Reynolds, T. J., & Phillips, C. B. (2005). In search of true brand equity metrics: All market share ain’t created equal. *Journal of Advertising Research, 45*(2), 171-186.

Rigdon, E. (2016). Choosing PLS Path modelling as an Analytical Method in European Management Research: A Realist Perspective. *European Management Journal, 34*(6), 598-605.

Ringle, C. M., Sarstedt, M., & Straub, D. W. (2012). Editor’s comments: A critical look at the use of PLS-SEM in MIS Quarterly. *MIS Quarterly, 36*(1), iii-xiv.

Rintamäki, T., Kanto, A., Kuusela, H., & Spence, M. T. (2006). Decomposing the Value of Department Store Shopping into Utilitarian, Hedonic and Social Dimensions: Evidence from Finland. *International Journal of Retail & Distribution Management, 34*(1), 6-24.

Rönkkö, M. (2014). The effects of chance correlations on partial least squares path modeling. *Organizational Research Methods, 17*(2), 164-181.

Rönkkö, M., & Evermann, J. (2013). A critical examination of common beliefs about partial least squares path modeling. *Organizational Research Methods, 16*(3), 425-448.

Rönkkö, M., McIntosh, C. N., & Antonakis, J. (2015). On the adoption of partial least squares in psychological research: Caveat Emptor. *Personality and Individual Differences, 87,* 76-84.

Rönkkö, M., McIntosh, C. N., Antonakis, J., & Edwards, J. R. (2016). Partial least squares path modeling: Time for some serious second thoughts. *Journal of Operations Management, 47,* 9-27.

Salazar-Ordóñez, M., Cordón-Pedregosa, R., & Rodríguez-Entrena, M. (2019). A consumer behaviour approach to analys Handmade and Locally Made Agrifood Products in Western Honduras. *Economia Agraria y Recursos Naturales*, *18*(2), 5-27.

Sanib, N. I. R., Aziz, Y. A., Samdin, Z., & Rahim, K. A. (2013). Comparison of marketing mix dimensions between local and international Hotel customers in Malaysia. *International Journal of Economics and Management, 7*(2), 297-313.

Sarstedt, M., Hair Jr, J. F., Cheah, J. H., Becker, J. M., & Ringle, C. M. (2019). How to specify, estimate, and validate higher-order constructs in PLS-SEM. *Australasian Marketing Journal*, *27*(3), 197-211.

Sasmita, J., & Suki, N. M. (2015). Young consumers' insights on brand equity. *International Journal of Retail & Distribution Management*, *43*(3), 276-292.

Satit, R. P., Tat, H. H., Rasli, A., Chin, T. A., & Sukati, I. (2012). The relationship between marketing mix and customer decision-making over travel agents: An empirical study. *International Journal of Academic Research in Business and Social Sciences*, *2*(6), 522-530.

Schivinski, B., & Dabrowski, D. (2016). The effect of social media communication on consumer perceptions of brands. *Journal of Marketing Communications*, *22*(2), 189-214.

Schivinski, B., Muntinga, D. G., Pontes, H. M., & Lukasik, P. (2019). Influencing COBRAs: the effects of brand equity on the consumer's propensity to engage with brand-related content on social media. *Journal of Strategic Marketing,* 29(1), 1-23.

Schuberth, F., Henseler, J., & Dijkstra, T. K. (2018). Confirmatory composite analysis. *Frontiers in Psychology, 9*, 1-14.

Shamami, R. B., & Kheiry, B. (2019). The Effect of the marketing mix and after-sales service toward brand equity. *Journal of Economics, Business, and Accountancy Ventura, 22*(1), 123-136.

Shekhar, S. K., & Raveendran, P. T. (2013). Role of packaging cues on consumer buying behavior. *International Journal of Engineering and Management Sciences, 4*(1), 61-69.

Simon, C. J., & Sullivan, M. W. (1993). The measurement and determinants of brand equity: A financial approach. *Marketing Science, 12*(1), 28-52.

Singh, M. (2012). Marketing mix of 4P's for competitive advantage. *Journal of Business and Management, 3*(6), 40-45.

Soper, D. S. (2019). *A priori sample size calculator for structural Equation models [Software]*. http://www. danielsoper. com/statcalc.

Temporal, P. & Lee, K.C. (2001). *Hi-tech hi-touch branding: Creating brand power in the age of technology*, Wiley (Asia), Singapore.

Tong, X., & Hawley, J. M. (2009). Measuring customer-based brand equity: Empirical evidence from the sportswear market in China. *Journal of Product & Brand Management*, *18*(4), 262-271.

Travis, D. (2000). *Emotional branding: How successful brands gain the irrational Edge.* New York: Crown Publishing Group

van Riel, A. C., Henseler, J., Kemény, I., & Sasovova, Z. (2017). Estimating hierarchical constructs using consistent partial least squares. *Industrial Management & Data Systems, 117*(3), 459-477.

Vogel, V., Evanschitzky, H., & Ramaseshan, B. (2008). Customer equity drivers and future sales. *Journal of Marketing*, *72*(6), 98-108.

Wilson, B., & Henseler, J. (2007). *Modeling reflective higher-order constructs using three approaches with PLS path modeling: A monte car comparison.* In Thyne, M., & Deans, K. R. (Eds), Conference Proceedings ANZMAC 2007, ANZMAC, Dunedin, 791-800.

Wold, H. (1982). Soft modeling: The basic design and some extensions. *Systems Under Indirect Observation: Part II.* North-Holland, Amsterdam, 1-54.

Wu, Y. L., & Li, E. Y. (2018). Marketing mix, customer value, and customer loyalty in social commerce: A stimulus-organism-response perspective. *Internet Research, 28*(1), 74-104.

Yongpisanphob., W. (2019). Thailand industry outlook 2019-21: Motorcycle industry. Krungsri Research. Retrieved from https://www.krungsri.com/bank/getmedia/76b59cf3-0a44-4e53-9ca2-990970389747/IO_Motorcycle_190529_EN_EX.aspx

Yoo, B., & Donthu, N. (2001). Developing and validating a multidimensional consumer-based Brand equity scale. *Journal of Business Research, 52*(1), 1-14.

Yoo, B., Donthu, N., & Lee, S. (2000). An examination of selected marketing mix elements and Brand Equity. *Journal of the Academy of Marketing Science*, *28*(2), 195-211.

Zeithaml, V. A. (1988). Consumer perceptions of price, quality, and value: A means-end model and synthesis of evidence. *Journal of Marketing*, *52*(3), 2-22.

Zeithaml, V. A., Berry, L. L., & Parasuraman, A. (1996). The behavioral consequences of service quality. *Journal of Marketing, 60*(2), 31-46.