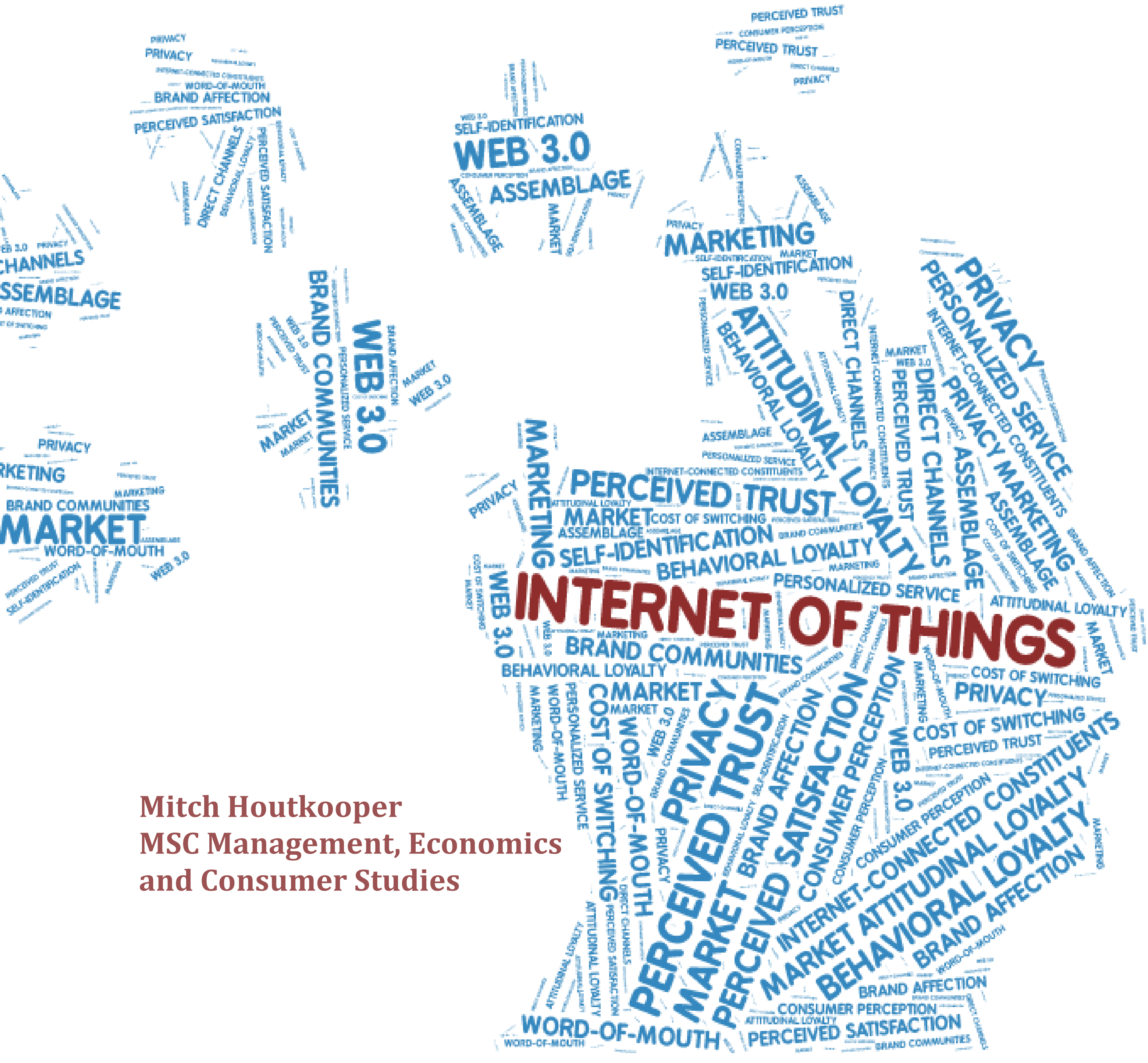
Can Internet of Things serve as an effective marketing endeavor in building brand loyalty?



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CAN INTERNET OF THINGS SERVE AS AN EFFECTIVE MARKETING ENDEAVOR IN BUILDING BRAND LOYALTY?

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ABSTRACT

The Internet of Things (IoT) is the next revolution of the web, and has the potential to change consumer brand experiences through 'interconnected smart items' (in this study conceptualized as *'assembled internet-connected constituents'*). Interactions between consumers and brands develop, because assembled internet-connected constituents acquire new capabilities that change the relationship between consumers and everyday items. The current study explores to what extent these emerging experiences influence behavioral brand loyalty (i.e. repeat purchases). An online experiment (N=255), testing consumers' brand loyalty of well-known sports brands was conducted. The results show that the total effect of brand experiences of assembled ICCs have significantly more influence on repeat purchasing, relatively to brand experiences without the implication of the Internet of Things. Although, the mediation effects of trust and satisfaction, and the moderation effect of attitudinal brand loyalty are not supported, it can be concluded that the Internet of Things can serve as an effective marketing endeavor in building brand loyalty.

Keywords: *Internet of Things, Assembled Internet-Connected Constituents, Brand Experience, Brand Trust, Brand Satisfaction, Behavioral Brand Loyalty, Attitudinal Brand Loyalty*

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1. INTRODUCTION

The *Internet of Things* (hereafter referred to as IoT) is developing as the next technological mega-trend (Jankowski et al., 2014). IoT is the buzzword for technology that enables physical objects to send and receive data via the internet (Rudman & Bruwer, 2016). This data traffic allows technology to create a cosmos where tangible goods are unified in digital information chains (Ng & Wakenshaw, 2016). It is expected that 24 billion 'everyday items' will be connected in 2020. Not only to the internet, but also to other items and devices, creating a giant interconnected web (Yan, Zhang & Vasilakos, 2014; Agrawal & Das, 2011; Meola, 2016). Physical, traditionally offline objects (e.g. clothing, cars, home appliances, etc.) that are interconnected via the internet are in this study indicated as *'Assembled Internet-Connected Constituents (ICCs)'* (Hoffman & Novak, 2015). For example, homeowners can identify on their smart device (i.e. smartphone or tablet) who arrived at their front, and grant visitors access to the residence, even without being home themselves. Thus, IoT technology enables formerly substantive everyday objects (in this example: the doorbell, security cameras, and the front door) to communicate via the internet as an assemblage, and work together to achieve things none could individually (Ng & Wakenshaw, 2016). Consequently, the identity transformation of these everyday objects leads to infinite changes of consumer brand experiences (Hoffman & Novak, 2015). Assembled ICCs influence brand experiences via convenience, transparency and traceability, switching costs, service improvements, real-time insights, and personalized products and services (Matthijsen et al., 2017).

ICCs allow businesses to recognize, collect and control user data of customers (Ng & Wakenshaw, 2016; Nunes & Gonçalves, 2017). Endless opportunities arise for firms that are able to use this data to drive relevant and compelling innovations (Murdoch & Johnson, 2016). Who customers are, what they need, and how they use products, can be utilized to provide relevant brand experiences (Matthijsen et al., 2017). The International Data Corporation estimates that digital conversions of products will be a major strategy for two-third of the Forbes Global 2000 companies in 2018 (Ring, 2017). Therefore, society will not escape the indomitable push of science and businesses in creating a smart world (Chowdhury & Dhawan, 2016). Prosperously, because IoT has the potential to stimulate global sustainable developments on social, environmental and economic level (Raftree, 2016). ICCs have the potential to be more convenient, to be perfectly energy efficient, and deliver endless opportunities for new business innovations (Bain, 2015).

In some progressive markets, like the sports apparel and consumer electronics markets, the first ICCs are already attainable on the market (Sainy, Gupta & Khasgiwala, 2011; Meola, 2016).

Probably no coincidence is that these markets are also eminent for its polygamous and brand loyal customers (Dawes, 2009; Sainy, Gupta & Khasigiwala, 2011). Generally, loyal customers have significant brand trust and are curious to new products and services of a specific brand (Reichheld & Schefter, 2000; Chudhuri & Holbrook, 2001; Gefen, 2002; Anderson & Srinivasan, 2003; Kim, Jin & Swinney, 2009).

However, the relation between '*the Web*' and brand loyalty has been a major tussle in marketing literature since the rise of e-commerce (Yadav & Pavlou, 2014). Brand loyalty becomes increasingly important, because the exponential growing market share of e-commerce causes far-reaching price pressure, making it very expensive to acquire new customers. While at the same time, the trend of declining brand loyalty expands fast (Matthijsen et al., 2017). First, the online market lacks face-to-face interactions, and the relation-building processes they encompass. Second, comparing competitor prices became suddenly much easier (Gefen, 2002). According to Deloitte, three out of four well-established consumer goods brands have to deal with diminishing 'must-have'[1] status of their products. These brands are constantly searching for ways to restore the lost connection with their consumers (Deloitte Pantry Study, 2015; Matthijsen et al., 2017). Therefore, the evolution of 'static web browsers' (*Web 1.0*) is often blamed for deteriorating brand loyalty (Srnivasan, Anderson, & Ponnavolu, 2002). The web turning into a more advanced social phase (*Web 2.0*) only partly resolved this problem (O'reilly, 2005; Mata & Quesada, 2014). Research showed that brand experiences of social networks, including branded social media, are primarily significant in enlarging *attitudinal brand loyalty* (e.g. positive word-of-mouth and the development of online brand communities), and only slightly stimulate *behavioral brand loyalty* (a.k.a. repeat purchases) (Laroche, Habibi & Richard, 2013; Hawkins & Prakash, 2013; Mata & Quesada, 2014). IoT is the next evolution of the internet, and often referred to as '*Web 3.0*' (Kolmann, Lomber, & Peschl, 2016; Rudman & Bruwer, 2016).

Most papers investigating the impact of IoT on consumer perceptions are focused on brand trust (e.g. Yan, Zhang & Vasilakos, 2014; Sicari et al., 2015; Murdoch & Johnson, 2016), while other papers investigated how it effects satisfaction (e.g. Yu et al., 2017; Dong, et al., 2017). Unmistakely, brand trust is an essential factor in defining consumer perceptions towards IoT. Mainly because research showed that security and privacy risks significantly influence consumer perceptions towards IoT experiences (Jin, Line, & Merkebu, 2016). However, acquiring trust has never been the end-goal in business, but only one of the factors influencing purchasing decisions of consumers. Yan, Zhang & Vasilakos (2014) argue that further research on IoT is conformed and driven by practical needs, because IoT products and services with seductive user experiences are

[1] 1 'Must haves' are products loyal consumers want irrespective of the price (Deloitte Pantry Study, 2015).

soon expected on the market. As mentioned, well-established brands in the online market have a practical need to restore behavioral brand loyalty (Deloitte Pantry Study, 2015). Additionally, Yu et al. (2017) highlight the importance of brand satisfaction for IoT products and services, by means that satisfaction derives from emotional affection towards brand experiences. Whereas current studies on trust in the IoT are generally describing cognitive-based trust towards the new experiences (e.g. Sicari et al., 2015; Murdoch & Johnson, 2016).

The hypothesis of this study is that brand experiences, emanated from assembled ICCs, have the ability to fundamentally change the relationship between consumers and brands, and can be a cornerstone in restoring behavioral brand loyalty for businesses. This report examines variables and relations between brand experience of assembled ICCs and behavioral brand loyalty by empirically testing a conceptual framework. To do so, the following research question is formulated:

"How do brand experiences of assembled Internet-Connected Constituents stimulate behavioral brand loyalty?"

Although, literature already provided some important implications on consumer perceptions towards IoT, the effect of new brand experiences on behavioral loyalty was not examined. This exploratory research tested this relation on behalf of an online experiment using the consumer sports market as a case study. The study adds ingenious thoughts on this still opaque, yet highly relevant research topic. The findings can be operated in marketing endeavors that stimulate behavior loyalty.

The next section of this paper contains a theoretical framework, which is conducted to investigate the essential components and relations between brand experiences of assembled ICCs and brand loyalty. The relations are defined as hypotheses. Subsequently, the key determinants and hypothesized relations are shown in a conceptual framework. In the third chapter of this thesis the research method is defined, followed by the results. Finally, the discussion and conclusion are given.

2. THEORETICAL FRAMEWORK

2.1 BRAND LOYALTY

The concept of brand loyalty has been introduced by (Copeland, 1923) and is acknowledged as a field of study in marketing for many decades (Howard & Sheth, 1969). Like the case for most other marketing concepts, there are many definitions of brand loyalty. Kotler & Keller (2006) define brand loyalty as *"the extent of consumer faithfulness towards a specific brand and this faithfulness is expressed through repeat purchases and other positive behaviors, irrespective of the marketing pressures generated by other competing brands".*

A brand is typically a title and a symbol that represents consumer perspectives on products and services (Kotler & Armstrong, 2004; Keller & Lehmann, 2006). The purpose of branding is to shape a positive image in the perception of consumers and to differentiate from major competitors (Kotler & Armstrong, 2004). Branding plays an essential role in determining marketing endeavors like positioning, new product development and advertising (Keller & Lehmann, 2006). Targeted branding provides meaningful contribution by obtaining an association of loyal customers (Ercis et al., 2012). These brand loyal customers are likely to spread positive word-of-mouth and have a high willingness-to-pay (Boulding et al., 1993; Bowen & Shoemaker, 1998; Tepeci, 1999). For businesses, brand loyalty is a cost-effective marketing practice and cuts down expenses that are affiliated with targeting new consumers (Kotler, Bowen, & Makens, 2003). Depending on the industry, retaining a customer is 5 to 25 times cheaper than acquiring a new one (Reichheld & Schefter, 2000).

2.1.1 A MULTI-DIMENSIONAL CONCEPT

Brand loyalty is a multi-dimensional concept, that can be evaluated in behavioral and attitudinal terms (Sheth & Park, 1974; Jacoby & Chestnut, 1978; Dick & Basu, 1994; Bowen & Chen, 2001; Worthington, Russell-Bennett & Härtel, 2010). In the definition of Kotler & Keller (2006), citated in the previous section, both behavioural and attitudinal perspectives are captured. Behavioural loyalty is "*brand faithfullness expressed through repeat purchases*", whereas attitudinal loyalty is the more ambiguous "*other positive behaviors*". Behavioral loyalty is important in an explicit matter, by means of revenues via repeat purchases, while attitudinal loyalty recuperates through psychological commitments, like intention to spread positive word-of-mouth and intention to join a brand community (Jacoby & Chestnut, 1978; Yu et al., 2017).

2.1.2 THE RELATIONSHIP BETWEEN BRAND EXPERIENCES AND BRAND LOYALTY

In the 90's the web opened its doors for businesses to target the global market. Fast network-based developments culminated in e-commerce via static web browsers (Web 1.0). Also, social networks (Web 2.0) are eminently influential on the online market (Mata & Quesada, 2014). These evolutions of the web emanated in new consumer brand experiences (Cyr, 2014). Nowadays, for brands involved in the retail and e-commerce markets, it is essential to understand the effect of brand experiences originating from IoT (Web 3.0) on consumer perceptions and behaviors (Meola, 2016).

According to Brakus, Schmitt & Zarantonnelo (2009) brand experiences are intuitive, internal consumer responses (cognitions, sensations and feelings) and behavioral responses stimulated by a brands' products, services and promotions. Brand experiences can emerge in behavioral (e.g. "I want to exercise"), sensory (e.g. "the fabric feels nice" and "visually warm"), affective (e.g. "enjoyable", "inspiring," and "pleasant remembrances") or intellectual (e.g. "I think of topics like animal wealth and labor standards", "reminds me to use my imagination") terms (Brakus, Schmitt & Zarantonello, 2009). Brand experiences occur when searching for products, purchasing products, receiving customer service, and using the products (Holbrook, 2000; Brakus, Schmitt & Zhang, 2008).

Online shopping, getting packages delivered at home, online (video) reviews, online service, and online brand information are examples of brand experiences deriving from Web 1.0 (Srnivasan, Anderson, & Ponnavolu, 2002). Cyr (2014) shows that satisfaction and trust are the most significant determinants of the relationship between brand experiences of the Web and loyalty. The effect of these brand experiences of static web browsers on online trust (Gefen, 2002; Koufaris, 2002) and online satisfaction (Agarwal & Venkatesh, 2002; Srnivasan, Anderson, & Ponnavolu, 2002) has been widely examined. However, "offline" brand experiences like face-to-face communication between consumers and brands declined (Srnivasan, Anderson, & Ponnavolu, 2002), while customer loyalty is mainly established via face-to-face interactions and the trust these services encompass (Gefen, 2002). Hence, the popularization of e-commerce is often blamed for deteriorating behavioral brand loyalty (Srnivasan, Anderson, & Ponnavolu, 2002).

Online brand communities and social media induced new brand experiences after the evolution of Web 2.0 (social networks) (O'reilly, 2012). The most successful brands were those that took best advantage of the new platforms providing the best service to its users. The service quality grew with the number of online brand followers, because of increased customer knowledge (Anderson, 2007). Google, Facebook and Youtube are popular applications that extent the services of static web browsers by including human-to-human communications. Consumers were suddenly more in charge of marketing, through online word-of-mouth and the emergence of online brand communities (Mata & Quesada, 2014). These brand experiences positively effected brand loyalty. Although, social networks have a higher probability of influencing attitudinal brand loyalty relatively to behavioral brand loyalty (Hawkins & Vel, 2013).

The present study investigates whether behavioral brand loyalty will increase because of the development and popularization of IoT. An important topic in the current market, because as a consequence of exponential increasing e-commerce and excessive competition on the web, the key for brands lies more in repeat purchases than in initial purchases (Meola, 2016). Behavioral brand loyalty comprises the competitive online market. Frequent purchases by a pool of brand benefactors, support fixed income for a specific brand (Smith, 2002). Before further elaborating on the relationship between brand experiences of IoT and behavioral loyalty, a consumer-focused conceptualization of IoT is presented.

2.2 WEB 3.0: CONSUMER PERSPECTIVE ON THE INTERNET OF THINGS

The term *Internet of Things* was first used by Kevin Ashton. As an employee of P&G, he had the idea that the use of 'radio-frequency identification' (RFID) might be useful in managing P&G's supply chain. In a PowerPoint presentation, Ashton described how *"adding sensors to everyday objects will create an Internet of Things, and lay the foundations of a new age of machine perception"* (Ashton, 2009).

IoT has flown out of the evolution of the world-wide web, and expands the internet by including human-to-object, object-to-human, and object-to-object connectivity and communication (Uckelmann, Harrison, & Michahelles, 2011; Rudman & Bruwer, 2016). IoT enhances Web 1.0 (static web browsers) and Web 2.0 (social networks) by adding constant connectivity, remote control ability and data sharing of physical objects (Peoples et al., 2013).

2.2.1. ASSEMBLAGES OF INTERNET-CONNECTED CONSTITUENTS

Wired physical objects are in this study indicated as *Internet-Connected Constituents* (ICCs). A set of ICCs is more than just a sum of the parts. The identity of the set arises from continuous synergies between individual ICCs (Hoffman & Novak, 2015). Complementarities are built between objects that were always considered substantive (Keskin & Kennedy, 2015). This consumer-focused perception of IoT originates from the De Landa (2006) 'assemblage theory'. According to the assemblage theory *"a component part of an assemblage may be detached from it and plugged into a different assemblage in which its interactions are different"* (De Landa, 2006). In other words, assemblage specifies that objects collaborate as a system, and operate in a way the objects could never accomplish individually (Hoffman & Novak, 2015).

In addition, the humongous amount of *data*, galvanized by increasing numbers of (inter)connected physical objects, are generating valuable *information* for businesses on their target group. *Knowledge*, obtained from the information, can be conducted in a demand-oriented way, where customer demand for products and services are at the center (Kolmann, Lomber & Peschl, 2016). The DIKW-pyramid (*figure 1*) can be finalized by transforming knowledge into *wisdom* via the inclusion of behavioral predictions (Nunes & Gonçalves, 2017).

FIGURE 1: DIKW PYRAMID (ROWLEY, 2007)

2.2.2 BRAND EXPERIENCES OF ASSEMBLED ICCS

IoT has led to webs of network-connected physical objects for society and consumers, including smart cities, smart homes and smart exercising (McKinsey, 2015). This third computing revolution affects brand experiences of consumers, because the essence of everyday objects changes (Li & Wang, 2013). As mentioned, brand experiences are intuitive, internal consumer responses and behavioral responses stimulated by a brands' products, services and promotions. Brand experiences emerge in behavioral, sensory, affective or intellectual terms (Brakus, Schmitt & Zarantonello, 2009). Brand experiences of assembled ICCs occur when searching for products, purchasing products, receiving customer service, and using the products (Holbrook, 2000; Matthijsen et al., 2017).

Matthijsen et al. (2017) listed three main brand experiences deriving from assembled ICCs. First, assembled ICCs are able to streamline daily life tasks and therefore increase convenience. Smart everyday objects can learn consumer preferences, predict needs and react dynamically to behaviour. Second, assembled ICCs deliver tracebility and transparancy of products. Infusing smart objects enables firms to provide their customers with personalized products and services. Brands are therefore able to offer their customers state-of-the-art and on data based products and services (Ng & Wakenshaw, 2016). Transparancy defects or necessary replacements can be easily measured and automatically dealt with. Also, it provides customers information on a product's provenance and carbon footprint. Third, assembled ICCs are able to provide real-time information and personal advise. Brands can shape brand experience by offering relevant advice that enlightens customers, and show them how to interact with the products (Matthijsen et al., 2017).

To illustrate, tennis apparel brands can serve their customers new experiences by offering assembled ICCs. The normally substantive clothes, shoes, tennis racquets and balls are because of IoT technology complementary in an assemblage (*figure 2*) (Keskin & Kennedy, 2015). IoT technology enables these ICCs to work together in measuring the sport performances of players. Real-time coaching is send through the headphones or smart watch to help the player improve technique and reduce chances of injury. After the work out, the corresponding mobile application provides feedback on the performances. The application informs which muscle groups should get more attention, and shows its user how to improve with the help of data from professional athletes. Additionally, the application offers new products corresponding with the needs and wants of the user.

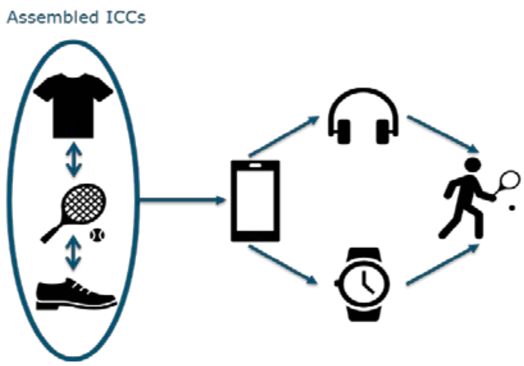

FIGURE 2: ASSEMBLED ICCS IN THE SPORTS APPAREL MARKET

2.3 THE RELATION BETWEEN BRAND EXPERIENCES OF ASSEMBLED ICCS AND BEHAVIORAL LOYALTY

In the online market, characterized by continuous growing competition, and behavioral loyalty at its lowest point, businesses are constantly searching for innovative ways to revitalize the lost connection with their customers (Matthijsen et al., 2017). This study assumes that brand experiences of assembled ICCs can restore deteriorated brand loyalty of businesses, because it positively effects repurchase decisions by virtue of three relations.

These relations are in accordance to Dick & Basu (1994) prominent customer loyalty model, elucidating that customer loyalty is influenced through cognitive, emotional and conative antecedents. Cognitive (e.g. accessibility and confidence) and emotional antecedents (e.g. emotions, feelings and moods) are largely equivalent to brand trust and brand satisfaction (Brakus, Schmitt & Zarantonello, 2009). These relations also correspond with several emperical studies that investigated the relationship between brand experiences of earlier developments of the web (Web 1.0 & Web 2.0) and brand loyalty. Laroche, Habibi & Richard (2013), Hawkins & Vel (2013), and Cyr (2014) verified that this relation is significantly mediated by internal brand perceptions trust and satisfaction.

However, not all brand experiences that result in repeat purchases are inferred by internal brand perceptions trust and satisfaction (Liu-Thompkins & Tam, 2013). These conative antecedents influence behavioral loyalty in a more concrete sense (Dick & Basu, 1994; Brakus, Schmitt & Zarantonnelo, 2009). Consumers may favor to repeat repurchase, because of brand experiences like convenience, habit or switching costs (Liu-Thompkins & Tam, 2013). Assumed is that conative antecedent 'cost of switching' is a primal influencer of behavioral brand loyalty.

2.3.1 BRAND EXPERIENCE: COST OF SWITCHING

Cost of switching is a well-known marketing strategy used to strengthen behavioral brand loyalty (Porter, 1980; Caruana, 2003). This strategy is effective when consumers need to make purchases elemental to a complementary system. For example, the cost of switching strategy is widely used in the razor market. The relatively large initial cost of buying a razor, is a mandatory factor in repeat purchase decisions of razor blades. In addition, consumer learning and lost time associated with changing brands applies to switching costs (Dick & Basu, 1994). With the development of Web 2.0 a new switching cost strategy emerged, the so-called 'data-trap'. Spotify has for example an effective data-trap strategy. If consumers want to switch from Spotify to another music app, consumers must accept the cost of losing their precious playlists (Amarsy, 2015). In IoT, these 'data-traps' could be implemented to everyday physical items. For example, assume that a consumer previously bought smart Nike shoes, and connected them to the Nike+ platform to track and share sport performances. Later, when this consumer decides to add a smart jersey to this specific assemblage, his choice is restricted due to businesses' unwillingness to share IoT services with major competitors (Busch, 2017). In summary, cost of switching is an additional brand experience incorporated with the utilization of ICCs, and positively influences repeat purchase intentions. According to this, the related hypothesis follows:

H1: Brand experiences of Assembled Internet-Connected Constituents have a positive effect on behavioral loyalty.

2.4 BRAND SATISFACTION

Brand satisfaction is defined as the "affective state that is the emotional reaction to a product or service experience" (Spreng, MacKenzi, & Olshavsky, 1996). In relation to repeat purchase intention, it is conceptualized as consumer evaluation based on all previous product and service experiences with a brand (Jones, Mothersbauch, & Beatty, 2000). Satisfaction is achieved when brand experience meets or exceeds consumer expectations (Rockwell, 2008). How can assembled ICCs increase brand satisfaction?

ICCs positively influence perceived satisfaction by providing services and products perfectly serving the needs and wants of consumers. Businesses can use data analysis to grant consumers with state-of-the-art products and services (Ng & Wakenshaw, 2016). An example how ICCs can increase brand satisfaction are Hewlett-Packard (HP) printers. HP's 'Instant Ink' service entails that the 'right, original HP-cartridges' are automatically delivered at the customers home, even before the old ones are completely empty (Dutch IT-channel, 2017). Another satisfaction increasing prosperity of assembled ICCs are their ability to enable enhanced user access and control (Kavis, 2014). For example, a smart home where a variety of household goods, such as lighting, locks, alarm camera's, televisions, and kitchen appliances, are tied together into complementary systems. With proper coordination of IoT, these connected objects could work together seamlessly, bringing greater efficiency, convenience and eventually enlarge consumer satisfaction (Weinburg et al., 2015). Last, infusing smart objects enables firms to adapt to the flourishing trend that consumers perceive higher satisfaction from experiences and personalized services relatively to physical materials. Real-time insights and personal advice can shape experience by providing applicable advice that enlightens customers (Matthijsen et al., 2017). For example, Babolat, a tennis racquet manufacturer offers tennis players real-time information and advice on their swing through their smart products in combination with a mobile application. The second hypothesis follows:

H2: Brand experiences of assembled Internet-Connected Constituents have a positive effect on brand satisfaction.

2.4.1. RELATION BETWEEN BRAND SATISFACTION AND BEHAVIORAL LOYALTY

Researchers who empirically examined the relationship between satisfaction and loyalty have found that satisfaction is a key determinant of brand loyalty (Bowen & Shoemaker, 1998; Anderson & Srinivasan, 2003; Flavian, Guinaliu, & Gurrea, 2006). According to Ercis et al., (2012) affective brand commitment as a result of perceived brand satisfaction eventually results in repeat purchase intention. Affective commitment is the emotional connection with a brand, and represents strong sense of personal identifications and shared values (Ercis et al., 2012). The relationship between satisfaction and brand loyalty seems to be intuitive (Anderson & Srinivasan, 2003); when customers are satisfied with previous purchases or services, they show emotional commitment by repeatedly buying the same brand (Ballantyne & Warren, 2006). The next hypothesis follows:

H3: Brand satisfaction has a positive effect on behavioral brand loyalty.

2.5 BRAND TRUST

Brand trust is a key element in relationships between firms and consumers (Hong & Cha, 2013). Trust is the willingness of a party to be sensitive to acts of another party based on the presumption that the other party carries out an activity in favor of the trustor, regardless of the capability to control that other party (Mayer, Davis, & Schoorman, 1995). In consumer-focused research the individual consumer represents the trustor and brands are the trustees. Since the shift in the common mode of shopping from offline to online, studies on consumer trust primarily focus on risk perceptions, such as privacy, online fraud, discrepancy in product and service quality, and delivery problems (Hong & Cho, 2011).

Brands should always respect and protect acquired personal data (Murdoch & Johnson, 2016), despite major opportunities to interchange Big Data for Big Money (Helbing, et al., 2017). According to Murdoch & Johnson (2016) 54% of the online consumers are careful about the information they share because of perceived uncertainty in the online security that should protect their user data. These consumer risk perceptions have an adverse impact on perceived trust (Jin, Line, & Merkebu, 2016). Currently, most papers on trust in IoT investigate how to technologically deal with privacy and security issues (Yan, Zhang, & Vasilakos, 2014; Sicari et al., 2015). However, from a consumer-focused perspective, brand trust also plays a pivotal role in helping consumers overcome perceptions of uncertainty and risk (Mayer, Davis, & Schoorman, 1995; Lin, 2011).

Brands that can build and sustain consumer trust will have the competitive advantage to convert data into wisdom instead of massive risks (Murdoch & Johnson, 2016). Kahneman & Tversky (1979) *Prospect theory* supports this assumption. Given that IoT technology is characterized by risk and uncertainty, the theory suggests that when choosing among several alternatives, people avoid losses and optimize for sure wins, because the pain of losing is greater than the satisfaction of an equivalent gain (Kahneman & Tversky, 1979). Therefore, if brand trust is built in a 'risky' market, consumers are less likely to switch to another brand (Chiu et al., 2012). As IoT matures, behavioral brand loyalty of businesses that participate in this market depend on the level of trust consumers have in them (Murdoch & Johnson, 2016). How can brands increase consumer trust via ICCs?

ICC user data can be utilized to advance and tailored business processes like product design, marketing, inventory management, new product development and customer services for loyal customers (Porter & Heppelmann, 2014). On behalf of data, brands can learn the needs and wants of their customers via direct B2C channels (Bauer & Latzer, 2016), and exploit the information in providing tailored products, services, and promotions, and in calculating product, service and maintenance demand (Ng & Wakenshaw, 2016). This has a beneficial impact on reliability, due to significant reduces of discrepancies in product and service quality, unwanted promotions, and delivery problems (Cisco, 2014). This could be seen as a switching cost, because switching costs are all important reasons not to switch to another brand. In this case, the switching costs are related to trust. In the perception of customers, purchasing products or services from other brands will lead to increased uncertainty and adverse consequences (Yen, 2010).

Furthermore, ICCs potentially enable consumers to access brand and product information, the items' origin and carbon footprint, and therefore check whether the product meets consumer sustainability and ethical standards. In the current market, concerns regarding unethical manufacturing eroded brand trust, therefore the ability to grant this transparency is critical in building trust (Matthijsen et al., 2017). The hypothesis follows:

H4: Brand experiences of assembled Internet-Connected Constituents have a positive effect on brand trust.

2.5.1. RELATION BETWEEN BRANDS TRUST AND BEHAVIORAL LOYALTY

Fast (online) market changes and the affiliated risks caused that perceived consumer trust is a key determinant of loyalty (Chaudhuri & Holbrook, 2001; Flavian, Guinaliu, & Gurrea, 2006; Lin & Wang, 2006). Trust via the affective route results in repeat purchases, because of shared values and customers' deep attachment (Ercis, et al., 2012). Enlarged risk perceptions, as a result of the development of the web magnified the importance of trust in repeat purchase decisions (Hong & Cho, 2011; Murdoch & Johnson, 2016). In addition, trust influences repeat purchases via an explicit, conscious thinking process (Vaisey, 2009; Kahneman, 2011; Kim, 2015). Trust that brands operate their activities in favour of their customers is determined as cognitive brand commitment (Hong & Cho, 2011). Cognitive brand commitment is based on consumer perceptions concerning a brands' competence, reliability, and dependability (Kim, 2015). The fifth hypothesis follows:

H5: Brand trust has a positive effect on behavioral brand loyalty.

2.6 ATTITUDINAL BRAND LOYALTY

The main goal to obtain behavioral loyalty, does not imply that attitudinal brand loyalty should be excluded. Attitudinal loyalty is highly relevant in the current online market since O'reilly (2005) first recognized that the web was turning into an advanced and more social phase (Web 2.0). The continuous development of social networks (Web 2.0) provokes that consumers are increasingly in charge of online marketing (Mata & Quesada, 2014). On account of human-to-human communications on the web, and new brand experiences like online brand communities, the importance of stimulating attitudinal loyalty increased for businesses (Cova & White, 2010; Hawkins & Vel, 2013). For example, Nike's community congregate around online platform Nike+. The content on Nike+ is created by the community on the platform and through various social media channels. Nike+ motivates followers to actively communicate with each other online, leading to enhanced attitudinal brand loyalty of the brand (Lobensommer, 2017).

Several papers acknowledging brand loyalty as a multi-dimensional concept, show that behavioral loyalty is a perceptible outcome of attitudinal loyalty (Dick & Basu, 1994; Chaudhuri & Holbrook, 2001; Bennet & Bove, 2002; Russell-Bennett & Härtel, 2010). Geçti & Zengin (2013) found that attitudinal loyalty of sport shoe brands positively influences behavioral loyalty. Thus, when consumers follow a brand on social media, spread positive word-of-mouth or join brand communities they are more likely to repurchase that brand. The hypothesis follows:

H6: Attitudinal brand loyalty has a positive effect on behavioral loyalty.

Furthermore, consumers perceive consumer word-of-mouth as more reliable than recommendations from product and service providers, and use them as important reference when making purchase decisions (Kuo, Hu, & Yang, 2013). Adjei, Noble & Noble (2010) found that online brand communities like Nike+ are effective commitment tools for retaining both long-term and newer customers. C2C communications that occur in online brand communities moderate between trust and repeat purchases via uncertainty reduction (Leisen & Prosser, 2004). "Uncertainty reduction theory" suggests that when interacting, people need information about the other party to reduce their uncertainty (Berger & Calabrese, 1975). Information spread in online C2C communications has a positive effect on behavioral loyalty, because it enhances feelings of trust (Leisen & Prosser, 2004). Royo-Vela & Casamassima (2011) show that belonging to a virtual community may enhance affective commitment towards the brand around which the community is developed. They found that active brand participation has a positive effect on repeat purchases, because it enhances feelings of satisfaction. In conclusion, consumers' positive internal perceptions (trust and satisfaction) are amplified when attitudinal brand loyalty is high, and therefore stimulate behavioral brand loyalty. This study proposes H7A and H7B as follows:

H7A: Attitudinal brand loyalty strengthens the relationship between brand satisfaction and behavioral brand loyalty.

H7B: Attitudinal brand loyalty strengthens the relationship between brand trust and behavioral brand loyalty.

2.7 CONCEPTUAL FRAMEWORK

Figure 3 illustrates the conceptual framework that guides the forthcoming study. The framework is a graphical representation of findings from the literature. The model includes multiple variables: an independent variable, a moderator/independent variable, mediator variables and a dependent variable. 'Brand Experiences of Assembled ICCs' is the consumer-focused conceptualization of the Internet of Things and the independent variable in this thesis. IoT technology enables that new webs of network-connected physical objects will be increasingly apparent in the upcoming years (McKinsey, 2015). This third computing revolution (Web 3.0) effects consumer purchasing behavior, because experiences of everyday objects change (Li & Wang, 2013). Behavioral loyalty is the dependent variable in the framework. Building brand loyalty has been a major issue for businesses since the popularization of e-commerce (Srnivasan, Anderson, & Ponnavolu, 2002). Therefore, businesses are constantly searching for innovative ways to revitalize the lost connection with their customers (Matthijsen et al., 2017). This thesis assumes that the implementation of assembled ICCs can be fundamental in restoring behavioral brand loyalty of established brands.

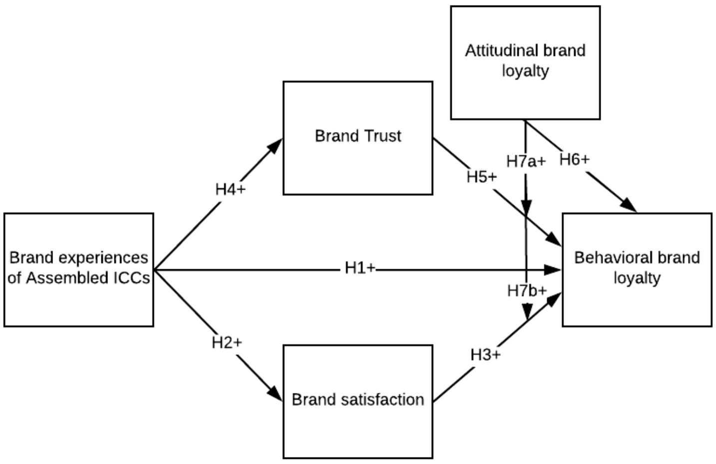

FIGURE 3: CONCEPTUAL FRAMEWORK

'Brand satisfaction' and 'brand trust' explain the relationship between the independent and dependent variables. ICCs positively influence perceived satisfaction by providing services and products perfectly serving the needs and wants of consumers (**H2**) (Ng & Wakenshaw, 2016). Consumers' emotional bonding with a brand that leads to repeat purchases is determined by brand satisfaction (**H3**) (Ballantyne & Warren, 2006). Due to enlarged consumer risk perceptions towards IoT, trust is a key determinant, because consumers are less likely to switch brands when brand trust is obtained (**H4** & **H5**) (Chiu et al., 2012). However, the mediation is incomplete, because additionally assumed is that practical advantages (like convenience and cost of switching) also play a fundamental role in affecting behavioral loyalty (**H1**) (Hayes, 2012). Data traps occur due to businesses their unwillingness to share services and data with competitors increasingly amplify switching costs of ICCs (Amarsy, 2015; Busch, 2017). Further, increased attitudinal loyalty of consumers, as a result of the popularization of social networks (Web 2.0), positively effects behavioral brand loyalty (**H6**) (Geçti & Zengin, 2013). Last, attitudinal brand loyalty has a moderating role in the conceptual framework. Due to the increasing popularization of social networks, the perceived reliability of word-of-mouth, and the impact of online brand communities, the relation between satisfaction/trust and repeat purchase decisions are moderated by a brands' attitudinal loyalty (**H7A** & **H7B**) (Cova & White, 2010; Kuo, Hu, & Yang, 2013). In other words, the effect of trust and satisfaction on repeat purchases can be enlarged by positive word-of-mouth and brand communities.

3. RESEARCH METHOD

The objective of the current research was to examine to what extent the implementation of assembled ICCs influenced behavior loyalty. An online experiment was conducted to compare the differences between the effects of 'brand experiences of assembled ICCs' and 'general experiences of the brands' on behavioral loyalty. Differences between the outcomes of the two groups showed how the development of assembled ICCs influence important consumer perceptions towards brands. On the basis of these differences, the research question was answered. Using the consumer sports market as a case study, the experiment granted important insights on the influence of brand experiences of assembled ICCs on trust, satisfaction and behavioral loyalty, and on the role of attitudinal brand loyalty. The experiment was arranged in English and set up in Qualtrics software.

3.1 PARTICIPANTS

The online experiment was conducted in December 2017, and yielded in 255 completed responses. The sample included 70 men and 185 women. The target population of this research were young adults (Millennials, born between the early 90's and the early 00's). This generation grew up in the information age, and had constant access to the growing technology (e.g. they accessed all stages of the Web (Web 1.0, Web 2.0 and Web 3.0). In other words, Millennials acceptation of new technology, can be seen as precursor of societies overall acceptance of new technology. These English speaking, early adopting, change agents of new technology are most easily found on universities.

3.2 PROCEDURE

The respondents were first introduced to the experiment. This initial page included some prior information. The expected completion time and the anonymity of the questionnaire were explained. Also, the respondents were informed that there were no 'right' or 'wrong' answers. At the end of the first page, respondents were thanked in advance for their participation. The first block of questions were regarding the gender, age, exercise frequency, and brand preference of the respondents. After these general questions, the respondents were equally divided in a test and a control group. Variables derived from the conceptual framework were examined through literature-based measures. Finally, a concluding page thanked the respondents for participating. The survey can be found in *Appendix I*.

3.3 DESIGN

The consumer sports market is used as a case study to test the conceptual framework, because in this market IoT technology is early adopted by consumers (Sainy, Gupta, & Khasigiwala, 2011; Meola, 2016). The first assembled ICCs in this industry are already attainable on the market, giving the respondents a clear understanding on what is meant with the independent variable. An additional advantage is that the target population is very health-conscious. According to Valentine (2017) almost four out of five Millennials exercises at least once a week. This increased the chance of obtaining usable data.

The sports apparel market is a monopolistic competition. This means that competing brands differentiate through physical products and marketing endeavors. Consequently, this study had to deal with existing consumer preferences to strengthen its internal validity. Tong & Hawley (2009) dealt with the same issue in emperically testing the brand equity of sport apparels. From the four listed brands used in that study, respondents were first asked to choose the brand they were most familiar with, and complete the rest of the questionnaire for that specific brand. This study copied that method, although it used a different selection question. The selection question from Eelen, Özturan & Verlegh (2017) better fitted this research. Eelen and her collegues asked their respondents how frequently (from 1- never to 6- frequently) they purchased fifteen different brands, and interviewed the respondents on one of the brands they most frequently bought. However, they distinguished the results for different brands, requiring over 1000 respondents to get valid results. Accordingly, this study asked the following multiple choice question: "Which of the following brands have you bought most frequently?". The six most valuable sports apparel brands (Nike, Adidas, Reebok, Under Armour, Puma and Asics) were obtained from Forbes. To ensure infalibility, a seventh option "I have not bought any of these brands before" was included to the question, excluding 34 respondents from the research.

3.4 BRAND EXPERIENCE MANIPULATION

The study had a one factorial (brand experience: assembled ICCs vs general) between-subjects design. The independent variable was conditioned and had two levels. The two conditions were treated the same, except for the instructions they received. The presented manipulation stimulated the test group to link the implementation of assembled ICCs to brand experiences with the brand. Assumed was that the ratings of brand experience measures were higher for the "assembled ICCs condition" (test group, N=105) than for the "general condition" (control group, N=116[2]).

Brand experiences are instructed to the test group with the help of *figure 4* and the following treatment/text: "(*Imagine that) X offers* ***smart*** *(internet-connected) clothing and accessories that can monitor sport performances in your favorite sport. X offers inter-connected shoes, shirts, socks, headphones, watches, all kinds of balls and rackets, etc. that work perfectly together to measure things like body temperature, amount of sweat, grip, speed, power, ground contact time, and body balance. Smart gear supports real-time coaching send to your headphones to help improve your technique and reduce chances of injury. After the work out, the corresponding mobile application of X (which only connects to smart products of X) provides feedback on your performances. The application informs which muscle groups should get more attention and shows how to improve your technique with the help of data from professional athletes*". *Additionally, the application of X advises new products and services that help customers achieving their goals. These advises are based on user data derived from the smart products and the application.* In the survey, X is replaced by the respondents' most frequently bought brand.

FIGURE 4: ASSEMBLED ICCS RUNNING APPAREL (BRIAR, 2016)

[2] Difference in N occurred because quite some respondents in the test group did not complete the survey.

3.5 VARIABLES

Manifest variables 'Gender' (X_1) and 'Exercise frequency' (X_2) were considered control variables in the study. Melnyk, van Osselaer & Bijmolt (2009) found that in the sports apparel market men are generally more brand loyal than women. Iwasaki & Havitz (2004) highlight that leisure involvement has significant effect on behavioral brand loyalty. Especially the frequency of doing a particular hobby or sport has been evaluated as an important factor. Therefore, it was assumed that the respondents' gender and their frequency of playing sports strongly influences the outcome, while remaining constant throughout the study.

The measures utilized to test the latent variables (F_1, F_2, F_3, F_4 & Y_1) were essential in obtaining reliable data. In searching for suitable measures, several aspects were therefore taken into consideration. First, the salient determinants in the study were all measured via well-established scales or subsets of scales previously used in influential marketing literature. Second, the measures had to be in accordance to the findings of the theoretical framework. Last, it was preferred that all measurements were tested according to the same scale. Most measures were slightly adapted, for example, "*I am satisfied with this brand's products*" (Oliver, 1997) was adapted to *"I am satisfied with products from X",* to correctly implement the respondents' preferred brand to the statement. An overview of the measures is presented in *Table 1* on *page 26*.

3.5.1 BRAND EXPERIENCE OF ASSEMBLED ICCS (F_1) & BRAND EXPERIENCE (F_1)

The measures for *Brand Experience of Assembled ICCs* (f_1 test group) and *Brand Experience* (f_1 control group) are obtained from Brakus, Schmitt, & Zarantonello (2009). According to this study, brand experience emerges in behavioral, sensory, affective and intellectual terms. Brakus and his colleagues created 3 measures for the 4 determinants of brand experience. For each determinant of brand experience, the measure with the highest 'goodness-of-fit' index is used as a measure in this study. For example, *"X makes a strong impression on my visual sense or other senses"* is the deputy of sensory brand experience. The respondents were asked to evaluate to what extent the 4 items were descriptive to their experience with their preferred smart brand. A 7-point Likert scale is used, where 1 was 'strongly disagree' and 7 was 'strongly agree'.

3.5.2 BRAND TRUST (F_2)

The measures for *Brand Trust* are obtained from McKnight, Choudhury & Kacmar (2002), in which they developed and validated trust measures for e-commerce. They distuinguished trust in three categories; benevolence, integrity and competence. Selected are the most suitable questions (on the basis of the theoretical framework) for each category. Following Oliveira et al. (2017) who also adopted the trust measurement from McKnight, Choudhury, & Kacmar (2002), this research used a 7-point Likert scale to measure if respondents agree with the statements, where 1 was ‘strongly disagree’ and 7 was ‘strongly agree’.

3.5.3 BRAND SATISFACTION (F_3)

Brand Satisfaction was measured with the help of Oliver (1997) ‘Consumption Satisfaction Scale’. Like Zboja & Voorhees (2006), this study used a subset of Oliver (1997) to measure satisfaction with a 7-point Likert scale. Supported by the theoretical framework, four appropriate satisfaction measures were chosen. Likewise, to what extent the respondents agree with the following statements is questioned.

3.5.4 ATTITUDINAL BRAND LOYALTY (F_4)

Muntinga, Moorman, & Smit (2011) did research to online brand activities, including the importance of online word-of-mouth and online brand communities. Four attitudinal behavioral activities derived from this study. Respondents had to indicate how likely it was that they would undertake these activities, based on a 7-point Likert scale (from 1- extremely unlikely to 7- extremely likely).

3.5.5 BEHAVIORAL BRAND LOYALTY (Y_1)

The measures for behavioral loyalty are derived from Helm, Eggert & Garnefeld (2009). This study is selected because it makes a clear distinction between attitudinal and behavioral loyalty, and used a 7-point Likert scale balancing the measures for this study. A 7-point Likert scale is used to measure if respondents agreed with the statements, where 1 was ‘strongly disagree’, and 7 was ‘strongly agree’.

TABLE 1: MEASURES FOR THE LATENT VARIABLES

Measurement	*Source*
Brand Experience of Assembled ICCs/Brand Experience (EXP) EXP1: X makes a strong impression on my visual sense or other senses. EXP2: X induces feelings and sentiments. EXP3: I engage in physical actions and behaviors when I use X. EXP4: I engage in a lot of thinking when I encounter X.	(Brakus, Schmitt, & Zarantonello, 2009)
Brand Trust (TRU) TRU1: I have confidence that X acts in my best interest. TRU2: I can rely on efforts from X to protect my personal information. TRU3: X is competent and effective in providing my needs and wants.	(McKnight, Choudhury, & Kacmar, 2002) (Oliveira, Alhinho, Rita, & Dhillon, 2017)
Brand Satisfaction (SAT) SAT1: I am satisfied with products from X. SAT2: Buying products from X is a wise decision. SAT3: I'm doing the right thing when buying a product from X. SAT4: I truly enjoy X products.	(Oliver, 1997) (Zboja & Voorhees, 2006)
Attitudinal Brand Loyalty (ABL) ABL1: Read customer opinions on X and their products online. ABL2: Following X on online brand community forums. ABL3: Watching review videos on X and their products. ABL4: Following X on social media.	(Muntinga, Moorman, & Smit, 2011)
Behavioral Brand Loyalty (BBL) BBL1: When shopping for sport apparels/consumer electronics next time, I'm going to buy products made by X. BBL2: I prefer to buy products of X over products from competitors. BBL3: I'm interested in new product made by X. BBL4: I refer products made by X to family and friends.	(Helm, Eggert, & Garnefeld, 2009)

3.6 ANALYSES

Structural equation modeling (SEM) was used to assess the models and the hypothesized relations. The analyses were conducted in RStudio (*version 0.99.902*), utilizing the Latent Variable Analysis (Lavaan) package. SEM is a dominant analytical tool for testing cause-effect-relationship models that include variables that cannot be directly observed, but derive from other variables (Rosseel, 2012). When the aim of the analysis is to obtain significant information on the determinants of a certain consumer perception, SEM is the technique of choice (Hair et al., 2014).

SEM comprises two sub models, a structural model (the inner model) and a measurement model (the outer model). The measurement model enumerates the effect of observed indicators on the latent variables. The structural model formulates the relationship between the independent, mediator, moderator and dependent variables. In *figure 5*, the structural model of the test model is visualized by a rectangle surrounding the variables, whereas the measurement model is exhibited by interrupted squares. The control model is identical, except for independent variable f_1, which is the unmanipulated 'Brand Experience'.

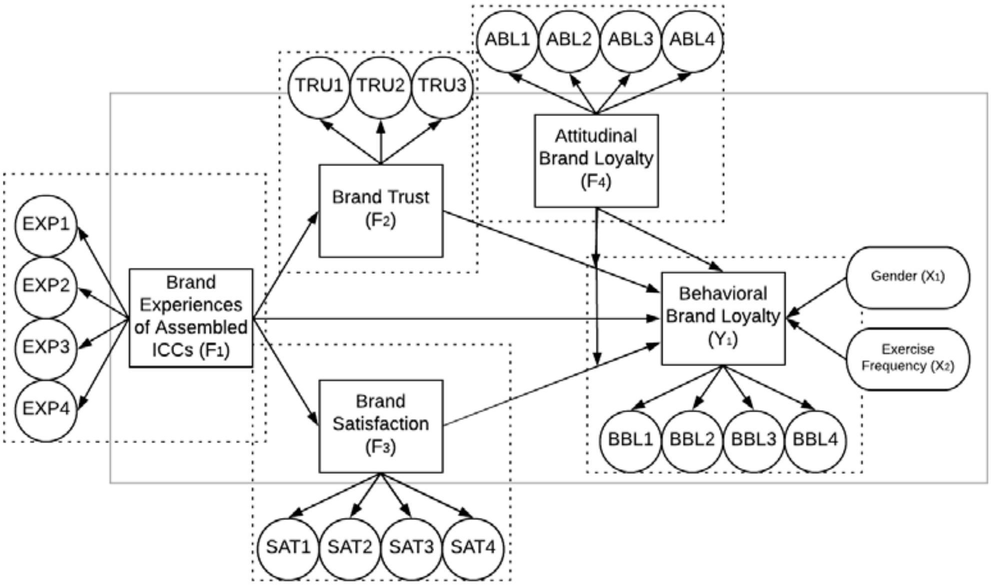

FIGURE 5: MEASUREMENT AND STRUCTURAL MODEL OF THE TEST GROUP IN A SEM DIAGRAM

First, a manipulation check was conducted to test whether the manipulation has worked. After, goodness-of-fit measures, reliability and validity tests were executed for both models (i.e. test model and control model). After the measurement models were optimized, the study performed the structural model assessments. The hypotheses were examined through regression analyses of the structural test model. Subsequently, the results of the test model were compared with the control model and literature. After, the research question *"how do assemblages of Internet-Connected Constituents stimulate behavioral brand loyalty?"* could be answered.

4. RESULTS

In the R environment, SEM in 'Lavaan' is used to test the hypotheses. Examining SEM comprises three stages. The three stags are: setting up the models, fitting the models, and examining the paths. Initially, a manipulation check was executed to test if the manipulation was effective.

4.1 BRAND EXPERIENCE MANIPULATION CHECK

A post hoc manipulation check illustrated that the "assembled ICCs manipulation" effectively primed independent variable f_1. All four measures (i.e. exp1, … exp4) showed higher means for the manipulated group relatively to the control group (see *Table 2*). Thus, the respondents who were exposed to assembled ICCs of their preferred brands perceived higher brand experiences in behavioral, sensory, affective and attitudinal terms. Also, dependent variable *Behavioral Brand Loyalty* (y_1), and mediators *Brand Trust* (f_2) and *Brand Satisfaction* (f_3) showed higher means for all indicators. It can be assumed that the manipulation succeeded.

TABLE 2: MEANS AND STANDARD DEVIATIONS OF THE INDICATORS

Latent Variable	**Indicator**	**Means test group (N=105)**	**Std**	**Means control group (N=116)**	**Std**
Brand Experience of Assembled ICCs (f_1)/ Brand Experience (f_1)	*EXP1: X makes a strong impression on my visual sense or other senses.*	*5.55*	*1.18*	*5.36*	*1.27*
	EXP2: X induces feelings and sentiments.	*4.85*	*1.36*	*4.40*	*1.24*
	EXP3: I engage in physical actions and behaviors when I use X.	*4.04*	*1.69*	*3.59*	*1.53*
	EXP4: I engage in a lot of thinking when I encounter X.	*3.74*	*1.71*	*3.21*	*1.44*
Brand Trust (f_2)	*TRU1: I have confidence that X acts in my best interest.*	*4.58*	*1.31*	*4.11*	*1.24*
	TRU2: I can rely on efforts from X to protect my personal information.	*4.51*	*1.30*	*4.22*	*1.14*
	TRU3: X is competent and effective in providing my needs and wants.	*5.23*	*1.07*	*4.86*	*1.01*
Brand Satisfaction (f_3)	*SAT1: I am satisfied with products from X.*	*5.93*	*0.89*	*5.84*	*0.73*
	SAT2: Buying products from X is a wise decision.	*5.47*	*1.06*	*5.24*	*1.16*
	SAT3: I'm doing the right thing when buying a product from X.	*4.93*	*1.22*	*4.53*	*1.20*
	SAT4: I truly enjoy this X products.	*5.52*	*1.16*	*5.32*	*0.97*
Attitudinal Brand Loyalty (f_4)	*ABL1: Read customer opinions on X and their products online.*	*4.57*	*1.79*	*3.91*	*1.90*
	ABL2: Following X on online brand community forums.	*3.04*	*1.82*	*2.65*	*1.53*
	ABL3: Watching review videos on X and their products.	*3.52*	*1.89*	*3.31*	*1.74*
	ABL4: Following X on social media.	*3.36*	*1.89*	*3.20*	*1.70*
Behavioral Brand Loyalty (y_1)	*BBL1: When shopping for sport apparels/consumer electronics next time, I'm going to buy products made by X.*	*4.71*	*1.30*	*4.32*	*1.37*
	BBL2: I prefer to buy products of X over products from competitors.	*4.26*	*1.64*	*4.09*	*1.62*
	BBL3: I'm interested in new product made by X.	*4.78*	*1.52*	*4.44*	*1.36*
	BBL4: I refer products made by X to family and friends.	*4.48*	*1.44*	*4.09*	*1.49*

4.2 MEASUREMENT MODEL

Following Henseler, Ringle and Sinkovics (2009), the measurement model assessed whether the conceptual framework of the two conditions fitted the data. The syntaxes for the measurement model of the two conditions are shown in *appendix II.* To determine the test model, latent variable *Brand Experience of Assembled ICCs* (f_1) was measured by manifest variables exp1, exp2, exp3 and exp4. For the control model, latent variable *Brand Experience* (f_1) was measured by manifest variables cexp1, cexp2, cexp3 and cexp4. The models were fitted with the cfa() function[3]. Summaries of the models were specified using the summary() function.

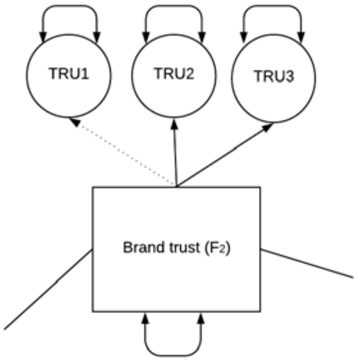

FIGURE 6: FRAGMENT OF THE MEASUREMENT MODEL

Figure 6 illustrates a fragment of the measurement model. The circles portray the manifest variables (hereafter referred to as 'indicators'). The dotted line means that the factor loading (intercept) of the first indicator was automatically fixed at 1, making it easier to interpret the results. Additionally, *figure 6* shows that in the measurement model the indicators and latent variables are also connected to themselves. This is implemented in the CFA() function to test individual reliability of all the variables (see *section 4.2.2*).

The measurement models were systematically assessed with goodness-of-fit measures, reliability and validity tests. Reliability and validity tests were already executed in the papers that presented the proposed measures. Nevertheless, these checks were repeated to assure its rightness in this study's context. Substantiation of the used methods and the rules of thumb of the reliability and validity tests can be found in *appendix III*. The main focus was on the fit of the manipulated model (i.e. The test model, N=105). Nevertheless, also the fit of the non-manipulated model (i.e. the control model, N=116) is provided.

4.2.1 GOODNESS-OF-FIT

Goodness-of-fit measures evaluate how sufficient a model fits a given data set (Kenny, 2015). McDonald & Ho (2002) suggest to examine multiple goodness-of-fit indices. The fit measures used for this study are: The Chi-square ($\chi 2$), the Comparative Fit Index (CFI), the Goodness of fit index (GFI), the Tucker-Lewis Index (TFI), the Standardized Root Mean Square Residual (SRMR), and the Root Mean Square Error of Approximation (RMSEA) (Hair, 1998; Hu & Bentler, 1999).

[3] CFA is confirmatory factor analysis (Rosseel, 2012).

In addition, in most statistical methods the p-value of the Chi-square supports the model when it is significant (p-value ≤ 0.05). However, in CFA the functions of H0 and H1 are swapped. HO indicates that the model fits the data, while H1 indicates that the model does not fit the data. In other words, H0 is the hypothesis that should be defended. Therefore, an insignificant chi-square confirms that the model fits the data (Blunch, 2015). *Table 3* shows the indices and their criterion for acceptance.

TABLE 3: SUMMARY OF THE TESTED GOODNESS-OF-FIT INDICES (HU & BENTLER, 1999)

Index	**Criterion for acceptance**	**Test Model**	**Control Model**
P-value (Chi-square)	P-value ≥ 0.05	***0.000***	***0.000***
Comparative Fit Index (CFI)	CFI value ≥ 0.90	*0.908*	***0.851***
Goodness of Fit Index (GFI)	GFI ≥ 0.90	***0.801***	***0.798***
Tucker-Lewis Index (TLI)	TLI ≥ 0.90	***0.891***	***0.824***
Standardized Root Mean Square Residual (SRMR)	SRMR ≤ 0.09	*0.064*	***0.094***
Root Mean Square Error of Approximation (RMSEA)	RMSEA ≤ 0.08	***0.085***	***0.093***

According to the output, the goodness-of-fit of the 19 indicators of the test model (i.e. exp1, exp2, …, bbl3, bbl4) did not completely load as expected (see *table 3*). Since the χ2 was significant (Chi-square = 253.938, p-value = 0.000, df = 145), the Tucker-Lewis and Goodness-of-Fit indices were lower than the tolerable threshold value of 0.90 (TLI = 0.891; GFI = 0.801), and the SRMR was higher than the tolerable threshold value of 0.08 (SRMR = 0.085). The other goodness-of-fit measures were accepted. The goodness-of-fit of the control model did not load as expected. None of the goodness-of-fit measures were accepted for this model.

4.2.2 RELIABILITY

4.2.2.1 INDIVIDUAL ITEM RELIABILITY

Analyses of the standardized factor loadings, standardized factor loadings squared and the standardized variances of the 19 indicators of both models proved significant indictor reliability for latent variables *Brand Trust* (f_2), *Brand Satisfaction* (f_3) and *Behavioral Brand Loyalty* (y_1). Nevertheless, for both models, *Brand Experience* (f_1) and *Attitudinal Brand Loyalty* (f_4) show some deficiency in indicator reliability. For the test model, the standardized factor loadings of f_1 were accepted, although, two out of four indicators were considered 'weak' (factor loadings ≤ 0.70) (Hair, 1998). Furthermore, indicator 'abl1' of f_4 was insignificant, while 'abl3' was weak. Subsequently, indicator 'abl1' was deleted from the measurement model (Hair, 1998). The values of f_1 and f_3 of the test model are shown in *Table 4*.

TABLE 4: INDIVIDUAL ITEM RELIABILITY OF THE TEST MODEL

Latent Variable	Indicator	Std. loadings	Std. loadings sq.	Std. Variances
Brand Experience of Assembled ICCs (f_1)	exp1	0.563	**0.316**	0.684
	exp2	0.671	0.451	0.549
	exp3	0.708	0.502	0.498
	exp4	0.700	0.489	0.511
Attitudinal Brand Loyalty (f_4)	**abl1**	**0.347**	**0.119**	**0.881**
	abl2	0.834	0.694	0.306
	abl3	0.628	**0.395**	0.605
	abl4	0.850	0.724	0.276

For the control model, two standardized factor loadings of f_1 (i.e. exp3 and exp4) were insignificant. Indicators 'exp1' and 'exp2' were considered 'weak' (factor loadings ≤ 0.70) (Hair, 1998). Furthermore, indicator 'abl1' of *Attitudinal Brand Loyalty* (f_4) was insignificant, while 'abl3' was considered weak. Indicators 'exp3', 'exp4' and 'abl1' were deleted from the model syntax. The values of f_1 and f_3 of the control model are shown in *Table 5.*

TABLE 5: INDIVIDUAL ITEM RELIABILITY OF THE CONTROL MODEL

Latent Variable	Indicator	Std. loadings	Std. loadings sq.	Std. Variances
Brand Experience (f_1)	exp1	0.683	0.467	0.533
	exp2	0.673	0.453	0.547
	exp3	**0.300**	**0.090**	**0.910**
	exp4	**0.473**	**0.223**	**0.777**
Attitudinal Brand Loyalty (f_4)	**abl1**	**0.500**	**0.250**	**0.750**
	abl2	0.804	0.646	0.354
	abl3	0.682	0.465	0.535
	abl4	0.815	0.664	0.336

4.2.2.2. INTERNAL CONSISTENCY RELIABILITY

The internal consistency of the test model was fine. The coefficients fell between ranges (0.7;0.8) and (0.8;0.9). The consistency of these coefficients were therefore respectively 'acceptable' and 'well' (Nunnely, 1978). Also, the internal consistency of the control model was fine. Except for latent variable *Brand Experience* (f_1) (α=0.663; Ω =0.606), which showed that the consistency of the coefficients were 'questionable' (Nunnely, 1978). The other coefficients were either 'acceptable' or 'well'. *Table 6* shows the α and the Ω (composite reliability) of the latent variables.

TABLE 6: INTERNAL CONSISTENCY RELIABILITY OF THE TWO MODELS

Model	Latent variable	Cronbach's Alpha	McDonald's Omega
Test Model	Brand Experience of Assembled ICCs (f_1)	0.783	0.721
	Brand Trust (f_2)	0.834	0.823
	Brand Satisfaction (f_3)	0.896	0.886
	Attitudinal Brand Loyalty (f_4)	0.769	0.753
	Behavioral Brand Loyalty (y_1)	0.858	0.862
	Total	0.924	0.937
Control Model	Brand Experience (f_1)	**0.663**	**0.606**
	Brand Trust (f_2)	0.744	0.774
	Brand Satisfaction (f_3)	0.826	0.832
	Attitudinal Brand Loyalty (f_4)	0.798	0.804
	Behavioral Brand Loyalty (y_1)	0.828	0.868
	Total	0.883	0.904

4.2.3 VALIDITY

4.2.3.1 CONVERGENT VALIDITY

For the test model, the Average Variance Extracted (AVE) of *Brand Experience of Assembled ICCs* (f_1) was lower than the threshold value of 0.5 (i.e. $f_1 = 0.458$). This means that the 4 indicators of this latent variable (exp1… exp4) lacked correlation within the latent variable. For the control model, the AVE of Brand Experience (f_1) was a lot lower than the threshold value (i.e. $f_1 = 0.154$). This means that the two remaining indicators of f_1 (exp3 and exp4) hardly correlated. *Table 7* shows the AVEs of the latent variables of the two models.

TABLE 7: AVERAGE VARIANCE EXTRACTED OF THE LATENT VARIABLES

Model	Latent variable	AVE
Test Model	Brand Experience of Assembled ICCs (f_1)	**0.468**
	Brand Trust (f_2)	0.619
	Brand Satisfaction (f_3)	0.692
	Attitudinal Brand Loyalty (f_4)	0.602
	Behavioral Brand loyalty (y_1)	0.608
Control Model	Brand Experience (f_1)	**0.154**
	Brand Trust (f_2)	0.529
	Brand Satisfaction (f_3)	0.574
	Attitudinal Brand Loyalty (f_4)	0.578
	Behavioral Brand loyalty (y_1)	0.568

4.2.3.2 DISCRIMINANT VALIDITY

TABLE 8: √AVE AND THE SHARED VARIANCES OF THE TEST MODEL

	f_1	f_2	f_3	f_4	y_1
f_1	0.684				
f_2	0.759	0.787			
f_3	0.750	0.569	0.832		
f_4	0.336	0.255	0.252	0.776	
y_1	0.803	0.627	0.666	0.365	0.780

TABLE 9: √AVE AND THE SHARED VARIANCES OF THE CONTROL MODEL

	f_1	f_2	f_3	f_4	y_1
f_1	0.392				
f_2	**0.642**	0.727			
f_3	**0.762**	0.589	0.758		
f_4	0.088	0.049	0.059	0.760	
y_1	**0.632**	0.238	0.594	0.398	0.710

Table 8 and *Table 9* show whether discriminant validity of the latent variables was established. The gray marked values on the diagonal are the √AVE, while the other factors represent the shared variances (squared correlations) between the latent variables. The outputs were examined with the Fornell-Larcker criterion. As shown in *Table 10*, the discriminant validity of the test model is sufficient for three latent variables. The AVE for *Brand Satisfaction* (f_3/f_3; 0.832) is greater than the shared variances between f_3 and the other latent variables. The same accounts for *Brand Trust* (f_2) and *Attitudinal Brand Loyalty* (f_4). However, the test output identified two cases with insufficient discriminant validity (i.e. f_1 and y_1). The √AVE for *Brand Experience of assembled ICCs* (f_1; 0.684) is lower than the shared variances between *Brand Experience of Assembled ICCs* (f_1) and *Brand Trust* (f_1/f_2; 0.759); *Brand Satisfaction* (f_1/f_3; 0.750); and *Behavioral Brand Loyalty* (f_1/y_1; 0.803). This means that latent variables f_2, f_3 and y_1 explain more of the variance in observed variables exp1, exp2, exp3 and exp4, than latent variable *Brand Experience of Assembled ICCs* (f_1). As a result, the model could not prove if these indicators were good measures for f_1. In other words, the discriminant validity of the test model is not established. This can have two explanations: (1) The strength of a relationship could be overestimated, or (2) a relationship may be confirmed when in fact there is no real relationship (Fornell & Larcker, 1981). Literature on the relationship between *Brand Experience of Assembled ICCs* and *Trust, Satisfaction* and *Behavioral Loyalty* suggest that the first scenario is more likely. A similar situation existed for latent variable y_1, although in that case only one shared variance was higher (f_1/y_1; 0.803). For the control model the discriminant validity of *Brand Experience* (f_1) and *Brand Satisfaction* (f_3) were

not accepted. The same conclusions can be drawn for the f_1 of this model. Although, the √AVE of independent variable f_1 of the control model is substantially lower.

Exploratory Factor Analysis (EFA) was executed to improve the discriminant validity. EFA is a helpful tool in finding out whether discriminant validity issues are the result of poorly performing indicators. Items that cross-load on more than one latent variable will be removed to increase the discriminant validity of the model, as well as weak items found in the reliability assessment. However, there should be a compromise between selecting the best measures and the total number of indicators used to measure a latent variable (Fornell & Larcker, 1981). In this study, three or four indicators per latent variables were preferred, with a minimum of two indicators.

4.3 EXPLORATORY FACTOR ANALYSES

The goal of the EFAs was to achieve 'simple structures', where each factor (latent variable) is represented by several indicators (preferably 3, minimum of 2) that strongly load on that factor only (Tabachnick & Fidell, 2007). With a sample size N>100, loadings of 0.40 or higher are considered strong. Complex indicators are indicators with loadings of 0.30 or higher on more than one factor (Kline, 2010). Oblique rotation (with the oblimin function) in EFA was used to identify weak and complex indicators of the test model, and orthogonal rotation (with the varimax function) was used to identify weak and complex indicators of the control model. Why these specific rotations were used, and the outputs of the EFAs are shown in *appendix IV*.

The factors of the test and control model accounted for respectively 55.7% and 55.4% of the variance. For both models, all factors were important, because the factors had eigenvalues > 1 (i.e. SS loadings test model: 4.132, 3.676, 2.774; SS loadings control model: 4.313, 2.740, 1.903 1.572). Also, the p-values were significant.

Following the EFA of the test model, tru1 (weak and complex), tru3 (complex), sat1 (complex) and sat4 (complex) were considered poorly performing indicators. However, as mentioned, it is preferred to keep three indicators per latent variable. Therefore, all possible models with and without the badly performing indicators were examined in accomplishing discriminant validity of the test model, while considering acceptable goodness-of-fit, reliability, validity and theoretical sense. Consequently, multiple CFAs and EFAs were executed. Following the EFA of the control model, sat4 (complex), bbl2 (complex) and bbl3 (complex) were poorly performing indicators. Indicator "sat4" could be deleted from the syntax, because three good performing indicators remained. However, all possible options with and without "bbl3" and "bbl4" were examined for the same reason as the test model.

Accordingly, the best fit for the test model was accomplished after deleting indicators tru1 ("I have confidence that X acts in my best interest), sat4 ("I truly enjoy products from X"), and abl1 ("Read customer opinions on X and their products online"). As a result, *Brand Trust* (f_2) is only measured by two indicators. However, this decision had to be made to achieve discriminant validity of the model. Fortunately, from a theoretical sense it can be justified. Indicator tru1 ("I have confidence that X acts in my best interest") is utterly similar to tru3 ("X is competent and effective in providing needs and wants"). The statistics also show quite some correlation (0.640) between these variables. The best fit for the control model was accomplished after deleting indicators sat3 ("I'm doing the right thing when buying a product from X") and bbl3 ("I'm interested in new product made by X").

4.4 CFA OF THE REVISED MODELS

4.4.1 GOODNESS-OF-FIT

In general, the fit statistics indicated a good fit for the improved models. However, the p-value of the Chi-Square remained 0.000, and was not accepted. A significant Chi-Square is the evidence that further research is necessary (Kline, 2010). Also, despite a clear improvement of the GFIs, the index remained under the threshold for both models (GFI test model= 0.842; GFI control model = 0.875). GFI compares 'degrees of freedom' with the sample size. One could conclude that for this model the degrees of freedom is too high for the number of samples. In conclusion, further research with larger sample sizes are needed to test whether the model correctly fits the data. *Table 10* shows the goodness-of-fit indices for the revised models.

TABLE 10: GOODNESS-OF-FIT INDICES OF THE REVISED MODELS

Index	**Criterions**	**Test Model**	**Control Model**
P-value (Chi-square)	p-value ≥ 0.05	***0.000***	***0.000***
Comparative fit index (CFI)	CFI value ≥ 0.90	0.930	0.932
Goodness of fit index (GFI)	GFI ≥ 0.90	***0.842***	**0.875**
Tucker-Lewis Index (TLI)	TLI ≥ 0.90	0.913	0.911
Standardized root mean square residual (SRMR)	SRMR ≤ 0.09	0.064	0.083
Root mean square error of approximation (RMSEA)	RMSEA ≤ 0.08	0.063	0.078

4.4.2 RELIABILITY

The individual indicator reliability of latent variables *Brand Trust (*f_2), *Brand Satisfaction* (f_3), and *Behavioral Brand Loyalty* (y_1) of the test model were good. Also, latent variables *Brand Experience* (f_1) and *Attitudinal Brand Loyalty* (f_4) improved. Nevertheless, the indicator reliability of exp1 (factor loading = 0.572) and abl3 (factor loading = 0.600) were not very well, although, greater than the threshold value of 0.55. The indicators remained in the model to ensure the discriminant validity, and to remain three indicators in Attitudinal Brand Loyalty (f4). The individual indicator reliability of the variables in the control model were generally good (factor loadings [0.7,0.9]). Three indicators (tru3 = 0.602; cexp2 = 0.656; abl3 = 0.634) were considered weak, although, quite far above the threshold value of 0.55.

The internal consistency reliability of the test model was good. The five latent variables exceeded the recommended threshold values of the Cronbach's Alpha and the McDonald's Coefficient Omega (0.7), showing evidence of internal consistency reliability. Also, four latent variables of the control model scored good internal consistency. However, latent variable *Brand Experience* (f_1) (α=0.663; Ω =0.606) still showed 'questionable' consistency. This means that it is questionable whether the scale yields consistent results when repeating the measurement. However, with only two indicators showing individual indicator reliability there were no possibilities in increasing internal consistency of f_1. The CFA outputs of the revised models can be found in *Appendix V.*

4.4.3 VALIDITY

For both models, all AVEs of the latent variables improved after deleting the weak and complex indicators. However, the AVEs of *Brand Experience of Assembled ICCs* (f_1 test model) and *Brand Experience* (f_1 control model) remained lower than the threshold value of 0.5 (i.e. f_1 test model = 0.465; f_1 control model = 0.479). This means that the indicators of these latent variables lack some correlation within the latent variable. Poor convergent validity within a set of indicators of the same factor suggests that the latent variable may lack indicators (Kline, 2010). Further research should increase the number of indicators that represent *Brand Experience (of Assembled ICCs)*. The AVEs can be found in *Appendix V*.

After excluding the weak and complex indicators from the test model, the √AVE of *Brand Experience* (f_1) and *Attitudinal Brand Loyalty* (f_4) increased, while shared variances between the latent variables decreased. As seen in the output, all standardized correlation values were lower than the √AVEs for the five latent variable. According to the Fornell-Larcker criterion, discriminant validity of the measurement model is accepted. *Table 11* shows discriminant validity of the revised test model.

TABLE 11: DISCRIMINANT VALIDITY OF THE TEST MODEL

	f_1	f_2	f_3	f_4	y_1
f_1	0.714				
f_2	0.653	0.787			
f_3	0.618	0.392	0.814		
f_4	0.317	0.201	0.442	0.776	
y_1	0.629	0.610	0.507	0.360	0.816

After excluding the weak and complex indicators from the control model, the √AVE of *Brand Experience* (f_1) and *Brand Satisfaction* (f_3) increased, while most shared variances between the latent variables decreased. A seen in *Table 12*, the shared variance between *Brand Experience* and *Brand Satisfaction* (f1/f3 = 0.857) increased. However, there was no better option available in fitting the control model. As seen in the output, the standardized correlation value f1/f3 was higher than the √AVEs for the two latent variables. According to the Fornell-Larcker criterion, discriminant validity of the control model is not accepted. In seeking measures for the f_1 -variable of the model, literature to 'Brand Experience of Assembled ICCs' was followed to compose the indicators. Therefore, it is not surprising that the fit of this latent variable (i.e. Brand Experience) is not great.

TABLE 12: DISCRIMINANT VALIDITY OF THE CONTROL MODEL

	f_1	f_2	f_3	f_4	y_1
f_1	0.692				
f_2	0.511	0.727			
f_3	**0.857**	0.438	0.785		
f_4	0.024	0.013	0.021	0.746	
y_1	0.517	0.220	0.546	0.130	0.781

4.5 STRUCTURAL MODEL AND TESTING THE HYPOTHESES

Structural Equation Modelling (SEM) was used to do regression analyses of the test model and evaluate the hypotheses. Additionally, regression analyses were executed for the control model. The control model enabled to study the effect of assembled ICCs on consumer perceptions towards brands. Therefore, the control group had an important role in answering the research question: *"How do brand experiences of assembled Internet-Connected Constituents stimulate behavioural brand loyalty?"*.

The structural test model was adapted to a set of 16 indicators. The structural control model was adapted to a set of 14 indicators. The syntaxes of the test and control model in RStudio are shown in *appendix VI*. *Figure 7* shows the structural test model, including named hypothesized paths. Except for variable f_1, the structural control model is identical.

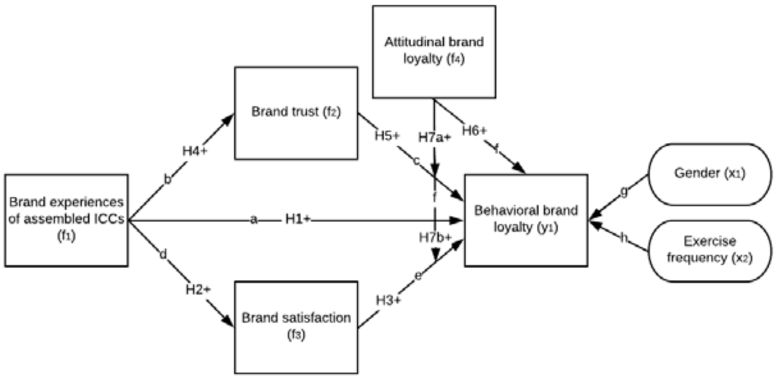

FIGURE 7: PATHS AND HYPOTHESES OF THE STRUCTURAL MODELS

Regressions:
*Behavioral Loyalty = i_1 + a*Brand Experiences + e_1*
*Brand Trust = i_2 + b*Brand Experiences + e_2*
*Brand Satisfaction= i_3 + d*Brand Experiences + e_3*
*Behavioral Loyalty = i_4 + b*Brand Experiences + (c*f)*Brand Trust + e_4*
*Behavioral Loyalty= i_5 + d*Brand Experiences + (e*f)*Brand Satisfaction + e_5*
*Behavioral Loyalty = i_6 + f*Attitudinal Loyalty + e_6*
*Behavioral Loyalty = i_7 + g*Gender + e_7*
*Behavioral Loyalty = i_8 + h*Exercise Frequency + e_8*

Where:
- *i_1, i_2, … i_7 and i_8 are intercepts,*
- *e_1, e_2, … e_7, and e_8 are residuals,*
- *a is the coefficient relating Brand Experiences of Assembled ICCs (f_1) and Behavioral Brand Loyalty (y_1),*
- *b is the coefficient relating Brand Experiences of Assembled ICCs (f_1) and Brand Trust (f_2),*
- *c*f is the moderated coefficient relating Brand Trust (f_2) (moderated by Attitudinal Brand Loyalty (f_4)) and Behavioral Brand Loyalty (y_1),*
- *d is the coefficient relating Brand Experiences of Assembled ICCs (f_1) and Brand Satisfaction (f_3),*
- *e*f is the moderated coefficient relating Brand Satisfaction (f_3)(moderated by Attitudinal Brand Loyalty (f_4)) and Behavioral Brand Loyalty (y_1),*
- *f is the coefficient relating Attitudinal Brand Loyalty (f_4) and Behavioral Brand Loyalty (y_1),*
- *g is the coefficient relating Gender (x_1) and Behavioral Brand Loyalty (y_1),*
- *h is the coefficient relating Exercise Frequency (x_2) and Behavioral Brand Loyalty (y_1),*

Total effect of Brand Experience of Assembled ICCs (f_1) on Behavioral brand loyalty (y_1) is:
- *a + b*(c*f) + d*(e*f)*

The structural test and control models were fitted using function sem() with bootstrapping the standardized error. There are several ways to test the significance of the study (e.g. test of joint significance or the Sobel test). For this study, the bootstrapping method is preferred, because it is assumed to be most precise for smaller sample sizes (Hair et al., 1998). In statistics, “bootstrapping involves repeatedly randomly sampling observations with replacement from the data set to compute the desired statistic in each resample. Thousand bootstrap resamples provide an approximation of the sampling distribution of the statistic of interest" (Preacher & Hayes, 1996). Bootstrapping delivers confidence intervals and point estimates. If the 95% confidence intervals of the relations do not cross zero, the paths are significant (Preacher & Hayes, 1996). The structural models were evaluated with function summary(). The fit of the structural test model is: P-value = 0.000, CFI = 0.928, TLI = 0.911, GFI = 0.840, SRMR = 0.067, RMSEA = 0.072. The fit for the structural control model is: P-value = 0.000, CFI = 0.925, TLI = 0.911, GFI = 0.867, SRMR = 0.079, RMSEA = 0.072. Before examining the significance of the paths and testing the hypotheses, the fit of the models are compared with a Chi-square difference test. Also the validity of the regressions (R^2) were evaluated.

4.5.1 THE CHI-SQUARE DIFFERENCE TEST

The Chi-Square Difference Test is used to whether a given model fits significantly better or worse than a competing model. If one of the two models fits significantly better, comparing the structural models would have little value. The control model has fewer parameters (i.e. 14 indicators) and therefore more degrees of freedom, than the test model (16 indicators). The difference in $\chi 2$ is 43.155. *Table 13* shows outcomes of the Chi-square difference test.

TABLE 13: CHI-SQUARE DIFFERENCE TEST

Model	$\chi 2$	*df*	RMSEA	CFI	Model comparison	Difference in $\chi 2/df$	Difference in RMSEA
Control Model	146.67	92	0.072	0.925	-	-	-
Test Model	189.82	123	0.072	0.928	2-1	43.155/31	0

A Chi-square table is used to find the p-value of the difference in $\chi 2/df$. The p-value of the difference is insignificant ($p > 0.05$). When the $\chi 2_{diff}$-value is insignificant, both models fit equally well statistically, so the control model can be accepted just as well.

4.5.2 COEFFICIENTS OF DETERMINATION (R^2)

TABLE 14: COEFFICIENTS OF DETERMINATION

Endogenous latent variable	R^2 Test Model	R^2 Control Model
Brand Trust (f_2)	*0.635*	*0.520*
Brand Satisfaction (f_3)	*0.617*	*0.833*
Behavioral Brand Loyalty (y_1)	*0.824*	*0.773*

R^2 measures validate the regression of the structural models (Hair et al., 2014). Henseler, Ringle, & Sinkovics (2009) suggest that in marketing studies R^2 values 0.75, 0.5, and 0.25 for endogenous latent variables can be described as respectively substantial, moderate and weak. The R^2 for

Behavioral Brand Loyalty (y_1= 0.824) means that the other latent variables (i.e. f_1, f_2, f_3 and f_4) of the test model explain 82.4% of the variance in y_1. The validity of the regression is confirmed for both models.

4.5.3 PATH COEFFICIENT ANALYSES TO TEST THE HYPOTHESES

The bootstrap method for the standard error was used to test the significance and coefficients of the (hypothesized) paths of the models. The path coefficients and confidence intervals are shown in *table 15* and *table 16.* In bootstrapping, it is common to use confidence intervals to test the significance of the paths (Henseler, Ringle, & Sinkovics, 2009).

TABLE 15: PATH COEFFICIENTS AND SIGNIFICANCE OF THE TEST MODEL

Hypothesis	Regression	Path	Unstandardized coefficient	Std. Error	Path coefficients (β)	ci.lower	ci.upper	supported/ not supported
1	**$f_1 \rightarrow y_1$**	A	*1.042*	*0.890*	*0.669*	*0.269*	*3.078*	Supported
2	**$f_1 \rightarrow f_2$**	B	*1.103*	*0.469*	*0.790*	*0.499*	*2.320*	Supported
3	**$f_2 \rightarrow y_1$**	C	*0.195*	*0.406*	*0.175*	***-0.539***	***0.611***	not supported
4	**$f_1 \rightarrow f_3$**	D	*0.832*	*0.317*	*0.763*	*0.369*	*1.604*	Supported
5	**$f_3 \rightarrow y_1$**	E	*0.057*	*0.431*	*0.040*	***-0.744***	***0.584***	not supported
6	**f_4 -> y_1**	f	*0.080*	*0.082*	*0.113*	***-0.101***	***0.229***	not supported
7a	**$f_2 * f_4 \rightarrow y_1$**	c*f	*0.016*	*0.059*	*0.020*	***-0.061***	***0.082***	not supported
7b	**$f_3 * f_4 \rightarrow y_1$**	e*f	*0.005*	*0.037*	*0.004*	***-0.077***	***0.077***	not supported
-	**$x_1 \rightarrow y_1$**	g	*-0.071*	*0.138*	*-0.030*	***-0.365***	***0.187***	not supported
-	**$x_2 \rightarrow y_1$**	h	*-0.100*	*0.095*	*-0.090*	***-0.295***	***0.069***	not supported

Notes:
H1 was supported. Brand experiences of assembled Internet-Connected Constituents have a positive effect on behavioral loyalty.
H2 was supported. Brand experiences of assembled Internet-Connected Constituents have a positive effect on brand satisfaction.
H3 was not supported. The study did not prove that brand satisfaction has a positive effect on behavioral brand loyalty.
H4 was supported. Brand experiences of assembled Internet-Connected Constituents have a positive effect on brand trust.
H5 was not supported. The study did not prove that brand trust has a positive effect on behavioral brand loyalty.
H6 was not supported. The study did not prove that attitudinal brand loyalty has a positive effect on behavioral loyalty.
H7a was not supported. The study did not prove that attitudinal brand loyalty strengthens the relationship between brand satisfaction and behavioral brand loyalty.
H7b was not supported. The study did not prove that attitudinal brand loyalty strengthens the relationship between brand trust and behavioral brand loyalty.

TABLE 16: PATH COEFFICIENTS AND SIGNIFICANCE OF THE CONTROL MODEL

Hypothesis	Regression	Path	Unstandardized coefficient	Std. Error	Path coefficients (β)	ci.lower	ci.upper	supported/ not supported
-	**$f_1 \rightarrow y_1$**	a	*0.420*	*19.017*	*0.353*	*-1.770*	*7.719*	not supported
-	**$f_1 \rightarrow f_2$**	b	*0.738*	*0.157*	*0.721*	*0.513*	*1.115*	Supported
-	**$f_2 \rightarrow y_1$**	c	*-0.068*	*4.295*	*-0.059*	*-0.741*	*0.349*	not supported
-	**$f_1 \rightarrow f_3$**	d	*0.598*	*0.086*	*0.913*	*0.454*	*0.785*	Supported
-	**$f_3 \rightarrow y_1$**	e	*0.730*	*26.783*	*0.403*	*-10.604*	*3.985*	not supported
-	**f_4 -> y_1**	f	*0.379*	*0.083*	*0.432*	*-1.770*	*7.719*	not supported
-	**f_2*$f_4 \rightarrow y_1$**	c*f	*-0.026*	*0.996*	*-0.025*	*-0.277*	*0.115*	not supported
-	**f_3*$f_4 \rightarrow y_1$**	e*f	*0.277*	*11.181*	*0.174*	*-4.383*	*1.545*	not supported
-	**$x_1 \rightarrow y_1$**	g	*-0.487*	*0.198*	*-0.205*	*-0.809*	*-0.117*	Supported
-	**$x_2 \rightarrow y_1$**	h	*-0.106*	*0.102*	*-0.089*	*-0.324*	*0.095*	not supported

The total effect (path: a + b*(c*f) + d*(e*f)) between *Brand Experience of Assembled ICCs* (f_1) and *Behavioral Brand Loyalty* (y_1) was significant (ci.lower= *0.399*; ci.upper= *3.099*) and positive (β = 0.668) in this consumer sports focused study. While the total effect between *Brand Experience* (f_1) and *Behavioral Brand Loyalty* (y_1) was insignificant (ci.lower= *-0.399*; ci.upper= *3.099*) and had a lower path coefficient (β = 0.494).

The participants' gender and their frequency of exercising were included in the models to account for additional brand preferences. However, the test data showed almost none variance and did not show significant influence on behavioral brand loyalty of the respondents towards their preferred sports brand (x_1: *β= -0.030, ci.lower = -0.365, ci.upper = 0.187;* x_2*: β= -0.090, ci.lower = -0.295, ci.upper = 0.069)*. The participants' gender was significant in the control model. Male respondents showed less behavioral brand loyalty relatively to the female respondents x_1: *β= -0.205, ci.lower = -0.089, ci.upper = -0.324*. This outcome contradicts with Melnyk, van Osselaer & Bijmolt (2009) study that suggests that in the sports apparel market men are generally more brand loyal than women.

Hypotheses 1 to 7b were tested through consideration of the path coefficients and their significance (ci.lower and ci.upper). The path coefficients of the test model were all positive (excluding the control variables). However, some paths had little effect (e.g. path *e* (*β* = 0.040); c**f* (*β* = 0.020); e*f (*β* = 0.004)). These paths were also insignificant. In addition, two path coefficients of the control model (brand trust → behavioral brand loyalty (*β* = -0.059, ci.lower = -0.741, ci.upper = 0.349); moderation effect of attitudinal brand loyalty on path c (*β* = -0.025, ci.lower = -0.277, ci.upper = 0.115)) showed insignificant negative path coefficients. The hypothesized paths of the test model are compared with same path of the control model, and with literature in the next chapter. To summarize, *figure 8 and 9* give a graphical representation of the significance and the path coefficients of respectively the test and the control model. The black lines show significant paths, while the red lines show insignificant paths.

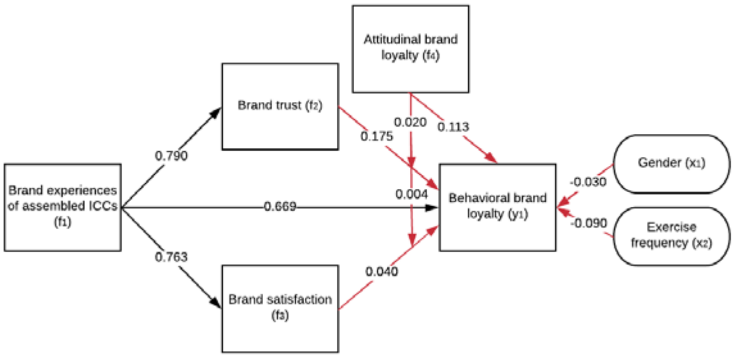

FIGURE 8: PATH ANALYSIS TEST MODEL

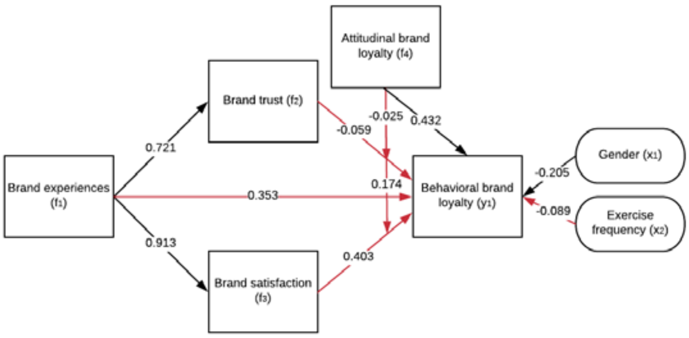

FIGURE 9: PATH ANALYSIS CONTROL MODEL

5. DISCUSSION

Even though many papers acknowledge the impact of IoT experiences on consumers, and many studies acknowledging the growing importance of behavioral loyalty in today's internet-focused society (Laroche, Habibi, & Richard, 2013), empirical research on the relationship between brand experiences of assembled ICCs and behavioral brand loyalty was missing. In order to be better understand the influence of the fast developing IoT industry on repeat purchasing behavior, a conceptual framework is developed and tested. The model relates four major components to behavioral brand loyalty: brand experiences of assembled ICCs, brand trust, brand satisfaction and attitudinal brand loyalty. A valuable target group has been questioned on their perceptions towards popular brands in a by 'IoT revolutionized consumer sports market'. In addition, non-manipulated respondents were examined in the same way to better profile the influence of assembled ICCs on the consumer perceptions. Structural equation modelling has been applied to examine the proposed relations. As a results, this paper provides valuable new insights on the effects of consumer brand experiences of IoT on behavioral loyalty.

The main hypothesis of the study: "… brand experiences, emanated from assembled ICCs, have the ability to fundamentally change the relationship between consumers and brands, and can be a cornerstone in restoring behavioral brand loyalty for businesses (see *p. 9*)" is supported. The total effect (path: a + b*(c*f) + d*(e*f)) between *Brand Experience of Assembled ICCs* (f_1) and *Behavioral Brand Loyalty* (y_1) was significant (ci.lower= *0.399*; ci.upper= *3.e099*) and positive (β = 0.668) in this study. While the total effect between *Brand Experience* (f_1) and *Behavioral Brand Loyalty* (y_1) path coefficient was weaker and insignificant (β = 0.494; ci.lower= *-0.399*; ci.upper= *3.099*). Furthermore, the manipulated respondents perceived more brand experiences, trust, satisfaction, and would be more inclined to repurchase the brand.

(H1) Brand experiences of assembled Internet-Connected Constituents have a positive effect on behavioral loyalty. The results show that the path coefficient between 'brand experiences of assembled ICCs' and 'behavioral brand loyalty' is significant and higher than the same insignificant path coefficient of the control model. Therefore, the current study is in compliance with the assumption that assembled ICCs change brand experiences in a way that repeat purchase behavior will be stimulated. Brand-related stimuli provoked by assembled ICCs experiences like 'switching costs', 'convenience', and 'personalized products' seem to influence repeat purchases without the repercussion of consumer perceptions trust and satisfaction.

(H2) Brand experiences of assembled internet-connected constituents have a positive effect on brand satisfaction. (H3) Brand satisfaction has a positive effect on behavioral brand loyalty. Both variables 'brand experiences of assembled ICCs' and 'brand experience' significantly influenced brand satisfaction (test model: β = 0.763, control model: β = 0.913). Although, it should be noted that the discriminant validity for this path was invalid in the control model. The results show that brand experiences of assembled ICCs are able to increase the satisfaction consumers obtain from a brand. This makes sense, because satisfaction is achieved when brand experience meets or exceeds consumer expectations (Rockwell, 2008). While under normal conditions the popular sports brands meet consumer expectations, assembled ICCs presumably exceed brand expectations of consumers (Ng & Wakenshaw, 2016). Overall, the manipulated respondents received higher brand satisfaction than the non-manipulated respondents. Probably because the manipulation showed respondents that assembled ICCs are able to perfectly serve the needs and wants of consumers. In both models, the positive, and in literature widely accepted relation

between brand satisfaction and behavioral loyalty were insignificant, and therefore not supported in this study.

(H4) Brand experiences of assembled Internet-Connected Constituents have a positive effect on brand trust. (H5) Brand trust has a positive effect on behavioral brand loyalty. Both variables 'brand experience of assembled ICCs' and 'brand experience' significantly influenced brand trust (test model: $\beta = 0.790$, control model: $\beta = 0.721$). As expected, both experiences of assembled ICCs and brand experiences in general lead to increased trust. Like brand satisfaction, the manipulated respondents have more trust in their favorite brand relatively to the non-manipulated respondents. Especially indicator tru3 ('*X is competent and effective in providing my needs and wants')* scored higher. Unsurprisingly, because the manipulation explained the respondents that personalized products and services are typical features of assembled ICCs. The test model showed an insignificant positive effect (β =0.175, ci.lower =-0.539, ci.upper = 0.611) of trust on behavioral loyalty. The widely accepted path between trust and behavioral loyalty in the control model showed an insignificant negative effect (β =-0.059, ci.lower = -0.741, ci.upper =0.349). The outcomes correspond with Chiu et al., (2012) study suggesting that when trust is built in the 'risky' market, consumers are less likely to switch to another brand. However, both paths were insignificant, therefore this theory is not supported.

(H6) Attitudinal brand loyalty has a positive effect on behavioral brand loyalty. Attitudinal brand loyalty was added to the conceptual model because Web 3.0 (the Internet of Things) is an extension of the Web 2.0 revolution (social networks). Literature suggested that the continuous development of social networks and the web provoked that attitudinal brand loyalty became increasingly important in the market (Mata & Quesada, 2014). It was therefore expected that loyalty would have a significant positive effect on behavioral loyalty. However, only the control model showed a significant positive effect between attitudinal and behavioral loyalty. Attitudinal brand loyalty (i.e. online brand communities, social media, online review videos) might become less important because IoT enables brands to connect more directly with individual consumers via ICCs.

(H7a) Attitudinal brand loyalty strengthens the relationship between brand satisfaction and behavioral brand loyalty. (H7B) Attitudinal brand loyalty strengthens the relationship between brand trust and behavioral brand loyalty. The moderation effects were not supported. The path coefficients of the moderations were close to zero and insignificant. These outcomes contradict to Leisen & Prosser (2004), who suggested that information spread in online C2C communications has a positive effect on behavioral loyalty, because it enhances feelings of trust. An explanation for the insignificance of this moderation effect is that the brands used in the experiment (e.g. Nike and

Adidas) are very well-known. When most respondents know a lot about a brand and their products, the effect of C2C communications (word of mouth, review videos, etc.) becomes more irrelevant. Royo-Vela & Casamassima (2011) state that active brand participation (e.g. joining an online brand community) has a positive effect on repeat purchases, because it enhances feelings of satisfaction. However, in general the respondents of the current study showed little interest in brand participation, causing an insignificant moderation effect of attitudinal loyalty.

6. LIMITATIONS & FURTHER RESEARCH

This study has several limitations that motivate further research. First of all, the study only involved six brands from the consumer sports market. Therefore, the outcomes of the study cannot be generalized to other upcoming IoT markets. Especially, if one considers that privacy and security concerns are major hurdles in the development of consumer IoT (Yan, Zhang & Vasilakos, 2014). Relatively to other data (e.g. financial data or personal communication), exercise data is considered less sensitive. Presumably, privacy and security issues will influence the relation between experiences of assembled ICCs and brand trust more than demonstrated in this study. Further research should focus on the effect of assembled ICCs on consumer perceptions in diverse markets.

Another limitation is the sample size of the experiment. In SEM, the sample size should be necessarily large. A model with approximately 15 indicators often has 200 – 400 cases (Hair, 1998). The total number of completed responses was 255. However, 34 respondents were excluded from the research, because this group indicated that they never bought any of the proposed brands. The remaining respondents were divided in two groups, that tested two models (test model (N=105); control model (N=116)). This resulted in some goodness-of-fit deficiencies. For both models, the Chi-Square ($\chi 2$) and the GFI indices showed poor fit. GFI compares 'degrees of freedom' (*df*) with the sample size . When GFI is lower the threshold value, the *df* is too high for the sample size. When $\chi 2$ is significant, further research is necessary to prove the fit of the model (Kline, 2010). Finally, it can be presumed relatively small sample sizes caused significant differences across subgroups, for examples male versus female respondents, and fanatic athletes versus non-athletes. In conclusion, larger sample sizes are needed to test whether the model correctly fits the data.

Furthermore, the measurement model showed some limitations. First, the 3 and 4-item scales of the latent variables had to be cut to obtain the reliability and validity of the two models. After deleting the weak and complex indicators, the reliability and of the test model were accepted. For the control model, 2 weak items (i.e., exp3 and exp4) of brand experiences (f_1) were removed in order to improve the fit of the measurement model. However, despite improving, the brand experience (f_1) scale still exhibited a lack of indicator reliability, convergent validity and discriminant validity. For further research it is advised to increase the number of indicators that represent brand experience.

Finally, the results of this study raise some additional questions, which should be answered through further research. The current study shows that millennials favor to repurchase a brand because of sensations, feelings, cognitions, and behavioral responses evoked by assembled ICCs. However, it remains unclear to what extent these different brand experience responses have a positive effect on behavioral loyalty. In addition, the unexpected insignificance of attitudinal brand loyalty on repeat purchasing behavior in the assembled ICCs scenario is not supported by literature. This could be an interesting topic for further research.

7. CONCLUSION

The purpose of the study was to determine how brand experiences of assembled ICCs stimulate repeat purchasing behavior. Most importantly, the direct effect between brand experiences and behavioural loyalty did significantly increase in the assembled ICCs condition. Thus, millennials favor to repurchase a brand because of sensations, feelings, cognitions, and behavioral responses evoked by assembled ICCs. Assembled ICCs evoke these responses through convenience, transparency and traceability, switching costs, service improvements, and personalized products. Therefore, the Internet of Things can serve as an effective marketing endeavor in building brand loyalty. In addition, this study shows that consumer IoT experiences significantly influence trust and satisfaction. However, assembled ICCs in the consumer sports market do not enlarge the importance of trust and satisfaction in stimulating behavioural loyalty. Lastly, this study shows that the significance of attitudinal brand loyalty (e.g. social media, online reviews, and online brand communities) on repeat purchasing behavior decreases with the popularization of consumer Internet of Things. This result is not substantiated by literature, and therefore stimulates further research.

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APPENDIX I: SURVEY

Start of Block: Introduction Block

Dear respondent,

First of all, thank you for your contribution in this research!

If you are between 18 and 25 years old and sufficient in the English language you are very welcome to participate in this research. The goal of this survey is to obtain consumer opinions on specific brands in the sport apparel market. The survey is completely anonymous. Also, there are no right or wrong answers, I'm only interested in your opinion. The questionnaire only take you about 5 minutes, and gives you a chance to win a €50,- bol.com voucher!

Please click '>>' to start the survey. Thanks again and good luck!

Mitch Houtkooper

End of Block: Introduction block

Start of Block: Control variables

How old are you?

____

What is your gender?

- O Male (1)
- O Female (2)

How often do you exercise/work out/play sports?

- O (Almost) never (1)
- O About once a week (2)
- O Two or three times per week (3)
- O Four or more times per week (4)

Which of the following brands have you bought most frequently?

O Nike (1)

O Adidas (2)

O Reebok (3)

O Under Armour (4)

O Asics (5)

O Puma (6)

O I have never bought any of these brands (7)

Skip To: End of Survey If Which of the following brands have you bought most frequently? = I have never bought any of these brands

End of Block: Control variables

Start of Block: Measures

Please read the following text and observe the image above.

(Imagine that) X offers **smart clothing and accessories** that can monitor sport performances **in your favorite sport**. X offers inter-connected shoes, shirts, socks, headphones, watches, all kinds of balls and rackets, etc. that work perfectly together to measure things like body temperature, amount of sweat, grip, speed, power, ground contact time, and body balance. Smart gear supports real-time coaching with feedback sent through to your headphones to help improve your technique and reduce chances of injury. After the work out, the corresponding mobile application of X (**which only connects to smart products of X**) provides feedback on your performances. The application informs which muscle groups should get more attention and shows how to improve your technique with the help of data from professional athletes. Additionally, the application of X advises new products and services that help customers achieving their goals. These advises are based on user data derived from the smart products and the application.

Answer the following questions on the basis of this text.

To what extent do you agree with the following statements?

	Strongly disagree (1)	Disagree (2)	Somewh at disagree (3)	Neither agree nor disagree (4)	Somewh at agree (5)	Agree (6)	Strongly agree (7)
X makes a strong impression on my visual sense or other senses. (1)	O	O	O	O	O	O	O
X induces feelings and sentiments. (2)	O	O	O	O	O	O	O
I engage in physical actions and behaviors when I use X (3)	O	O	O	O	O	O	O
I engage in a lot of thinking when I encounter X(4)	O	O	O	O	O	O	O

To what extent do you agree with the following statements?

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I am satisfied with products from X (1)	O	O	O	O	O	O	O
Buying products from X is a wise decision. (2)	O	O	O	O	O	O	O
I'm doing the right thing when buying a product from X. (3)	O	O	O	O	O	O	O
I truly enjoy X products. (4)	O	O	O	O	O	O	O

To what extent do you agree with the following statements?

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I have confidence that X acts in my best interest. (1)	O	O	O	O	O	O	O
I can rely on efforts of X to protect my personal information. (2)	O	O	O	O	O	O	O
X is competent and effective in providing my needs and wants. (3)	O	O	O	O	O	O	O

How likely is it that you undertake the following activities?

	Extremely unlikely (1)	Moderately unlikely (2)	Slightly unlikely (3)	Neither likely nor unlikely (4)	Slightly likely (5)	Moderately likely (6)	Extremely likely (7)
Read customer opinions on X and their products online. (1)	O	O	O	O	O	O	O
Following X on online brand community forums. (2)	O	O	O	O	O	O	O
Watching review videos on X and their products. (3)	O	O	O	O	O	O	O
Following X on social media. (4)	O	O	O	O	O	O	O

To what extent do you agree with the following statements?

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
When shopping for sport apparels, I'm going to buy products made by X (1)	O	O	O	O	O	O	O
I prefer to buy products from X over products from competitors. (2)	O	O	O	O	O	O	O
I'm interested in new products made by X (3)	O	O	O	O	O	O	O
I will refer products made by X to family and friends. (4)	O	O	O	O	O	O	O

End of Block: Test Group

Start of Block: Conclusion

Thank you for participating in my research. Thanks to you, my graduation came another step closer. Every additional respondent for this survey, means that the relevance of the study increases. Therefore, I would like to ask if you want to share this questionnaire with friends? Please share the link below:

https://wur.az1.qualtrics.com/jfe/form/SV_6nZqPUB7199VofH

Any questions regarding the questionnaire can be asked via: mitch.houtkooper@wur.nl.
If you want a chance to win the €50,- voucher of bol.com, insert your e-mail below.
Don't forget to submit the survey by clicking on ">>".

____

End of Block: Conclusion

APPENDIX II: THE MEASUREMENT MODEL SYNTAXES

```
#Test Group Measurement Model
myModel <-'
y1 ~ f1 + f2 + f2*f4 + f3+ f3*f4 + f4
f2 ~ f1
f3 ~ f1

#measurement model test group
f1 =~ exp1 + exp2 + exp3 + exp4
f2 =~ tru1 + tru2 + tru3
f3 =~ sat1 + sat2 + sat3 + sat4
f4 =~ abl1 + abl2 + abl3 + abl4
y1 =~ bbl1 + bbl2 + bbl3 + bbl4'


#Control Group Measurement Model
myModelC <-'
y1 ~ f1 + f2 + f2*f4 + f3+ f3*f4 + f4
f2 ~ f1
f3 ~ f1

#measurement model test group
f1 =~ cexp1 + cexp2 + cexp3 + cexp4
f2 =~ ctru1 + ctru2 + ctru3
f3 =~ csat1 + csat2 + csat3 + csat4
f4 =~ cabl1 + cabl2 + cabl3 + cabl4
y1 =~ cbbl1 + cbbl2 + cbbl3 + cbbl4'
```

APPENDIX III: VALIDITY AND RELIABILITY SUBSTANTATION AND CRITERIA

Reliability analyses examine the degree of consistency between the measurements of a variable. It answers the question: "Does a scale yield consistent results when repeating the measurement?" (Hair, 1998). In judging how well latent variables are measured by their indicators, analysts need to distinguish between reflective and formative measurement models. This study used reflective models, because the latent variables are positioned as the common cause that flow to the indicators (Diamantopoulos & Siguaw, 2006). In other words, the manipulation of the latent variables causes the change of the indicators. For reflective models, it is common that 'Indicator Reliabilility' and 'Internal Consistency reliability' are assessed (Hair et al., 2014). *Table 3* shows the reliability analyses reported in this study.

TABLE 17: RELIABILITY ASSESSMENTS OF THE REFLECTIVE INDICATORS

Criterion	**Acceptable values**
Individual item reliability	Factor loadings ≥ 0.55 are statically significant (in a study with N ≥ 100). Factor loadings under the threshold value should be deleted (Hair, 1998).

	Indicator reliability exists when squared standardized factor loadings ≥ 0.40 (Bagozzi & Yi, 1988) .
Composite reliability/ McDonald's (1999) coefficient omega	Coefficients ≥ 0.70 are internally consistent (Hulland, 1999). Coefficients ≤ 0.60 lack internal consistency (Nunnely, 1978).

Validity analyses examine whether a set of measures accurately show the concept of research. It answers the question: "Is the scale measuring what it is intended to measure?" (Hair, 1998). Before examing the structural models and testing the hypotheses, it is fundamental to first test whether a model is reasonably correct. This can be measured by means of *'convergent validity'* and *'discriminant validity'* (Kline, 2010). If convergent validity does not meet the requirements, the indicators within the latent variable do not correlate well with each other. If the discriminant validity does not meet the requirements, indicators correlate more with other indicators outside the 'parent' latent variable than with the variables within their parent factor (Kline, 2010; Hair et al., 2014). Without conformed discriminant validity, it is uncertain whether confirmed hypothesized paths are genuine or the result of statistical discrepancies (Fornell & Larcker, 1981). *Table 8* shows the acceptable values of the validity tests.

TABLE 18: VALIDITY ASSESSMENTS OF THE CONCEPTUAL FRAMEWORK

Criterion	**Acceptable values**
Convergent validity	Average Variance extracted (AVE) of all latent variables > 0.50 (Kline, 2010)
Discriminant validity	Square root of AVE for al latent variable > the correlations between that indicator and other indicators (Fornell & Larcker, 1981).

APPENDIX IV: EXPLORATORY FACTOR ANALYSIS (EFA)

Exploratory Factor Analysis (EFA) uses mathematics to find complex patterns between variables (Child, 2006). These complex patterns can be found with the help of factor rotation. Yaremko et al. (1986) defined factor rotation as: "*In factor analysis, rotation of the factor axes (dimensions) identified in the initial extraction of factors, in order to obtain simple and interpretable factors*". The first step of factor rotation in EFA is to determine the number of factors (Kline, 2010). The Fa.parallel function determined that the number of factors of the test model was three, and the number of factors for the control model was four. In addition, rotation can be executed via orthogonal (i.e. assumed is that the factors are uncorrelated) or oblique rotation (i.e. assumed is that the factors are correlated). Tabachnick and Fiddell (2007) argue that oblique rotation, using the direct oblimin method, should be initially performed. If the factor correlations are around 0.32 or above (see factor correlations below), the results of oblique rotation are more accurate than the results of orthogonal rotation. The output of the oblique rotation function of the test model showed results larger than 0.32 for the test model, therefore oblique rotation was used. The output of the control model showed more results that were below the threshold value, therefore orthogonal rotation was used. Tabachnick and Fiddell (2007) argue that that the varimax method should be used for orthogonal rotation.

Factor Correlation Test Model:

```
           factor1    factor2    factor3
factor1  1.0000000 -0.3322276 -0.4890393
factor2 -0.3322276  1.0000000  0.6870820
factor3 -0.4890393  0.6870820  1.0000000
```

Factor Correlation Control Model:

```
          factor1    factor2    factor3   factor4
factor1 1.0000000 0.18024349 0.44748801 0.2820833
factor2 0.1802435 1.00000000 0.04625205 0.2016354
factor3 0.4474880 0.04625205 1.00000000 0.1335709
factor4 0.2820833 0.20163544 0.13357093 1.0000000
```

Standardized Rotated Factor Loadings Test Model:

```
    factor1 factor2 factor3
abl2 -0.899
abl4 -0.736
abl3 -0.574
sat2           0.929
sat3 -0.146   0.803
sat1  0.112   0.635   0.303
sat4 -0.131   0.593   0.305
tru2 -0.125   0.532   0.122
tru3          0.435   0.413
tru1          0.399   0.300
bbl2                  0.820
bbl1                  0.775
exp1  0.158           0.632
bbl3 -0.136           0.626
exp4 -0.240           0.624
exp2          0.179   0.552
exp3 -0.190           0.529
bbl4 -0.241   0.108   0.491

               Factor1 Factor2 Factor3
SS loadings      4.132   3.676   2.774
Proportion Var   0.217   0.193   0.146
Cumulative Var   0.217   0.411   0.557

Test of the hypothesis that 3 factors are sufficient.
The chi square statistic is 203.41 on 117 degrees of freedom.
The p-value is 1.3e-06
```

Standardized Rotated Factor Loadings Control Model:

```
     factor1 factor2 factor3 factor4
csat1  0.748  -0.262  0.121
cbbl1  0.719   0.163
csat2  0.708  -0.245  0.215
csat4  0.688
cbbl2  0.646   0.305
```

```
cbbl4  0.632   0.272
cexp1  0.588  -0.156   0.122
cbbl3  0.512   0.441  -0.190  0.105
ctru3  0.456           0.291
csat3  0.412           0.379
cexp2  0.400           0.267  0.139
cabl2          0.823   0.133
cabl4  0.170   0.738
cabl3          0.680
ctru2                  0.814
ctru1  0.115   0.184   0.684


               Factor1 Factor2 Factor3 Factor4
SS loadings      4.313   2.740   1.903   1.572
Proportion Var   0.227   0.144   0.100   0.083
Cumulative Var   0.227   0.371   0.471   0.554

Test of the hypothesis that 4 factors are sufficient.
The chi square statistic is 143.1 on 101 degrees of freedom.
The p-value is 0.00375
```

APPENDIX V: RELIABILITY AND VALIDITY OUTPUTS OF THE REVISED MODEL

```
Factor loadings (Std.all) of the test model:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  f1 =~
    exp1              1.000                               0.674    0.572
    exp2              1.366    0.258    5.303    0.000    0.921    0.679
    exp3              1.757    0.324    5.429    0.000    1.185    0.704
    exp4              1.790    0.328    5.457    0.000    1.208    0.710
  f2 =~
    tru2              1.000                               0.940    0.725
    tru3              1.075    0.136    7.886    0.000    1.010    0.951
  f3 =~
    sat1              1.000                               0.739    0.833
    sat2              1.216    0.126    9.654    0.000    0.898    0.854
    sat3              1.251    0.147    8.486    0.000    0.924    0.762
  f4 =~
    abl2              1.000                               1.485    0.820
    abl3              0.761    0.124    6.142    0.000    1.130    0.600
    abl4              1.116    0.133    8.385    0.000    1.656    0.882
  y1 =~
    bbl1              1.000                               1.052    0.814
    bbl2              1.213    0.137    8.844    0.000    1.275    0.781
    bbl3              1.135    0.126    8.975    0.000    1.194    0.790
    bbl4              1.005    0.123    8.196    0.000    1.056    0.737


Factor loadings (Std.all) of the control model:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  f1 =~
    cexp1             1.000                               0.919    0.724
    cexp2             0.884    0.138    6.405    0.000    0.812    0.656
  f2 =~
    ctru1             1.000                               0.942    0.761
    ctru2             0.931    0.136    6.854    0.000    0.877    0.776
    ctru3             0.644    0.113    5.720    0.000    0.606    0.602
  f3 =~
    csat1             1.000                               0.605    0.828
    csat2             1.557    0.161    9.650    0.000    0.941    0.814
    csat4             1.133    0.139    8.173    0.000    0.685    0.713
  f4 =~
    cabl2             1.000                               1.240    0.812
```

```
    cabl3              0.884    0.135    6.541    0.000    1.096    0.634
    cabl4              1.137    0.143    7.933    0.000    1.410    0.833
  y1 =~
    cbbl1              1.000                               1.082    0.785
    cbbl2              1.211    0.139    8.681    0.000    1.310    0.804
    cbbl4              1.034    0.128    8.058    0.000    1.119    0.748
```

```
Internal Consistency Reliability of the test model:
             f1        f2        f3        f4        y1     total
alpha 0.7831672 0.8068471 0.8437655 0.8046705 0.8576747 0.9152823
omega 0.7321091 0.8078979 0.8532040 0.8175246 0.8610969 0.9271053
```

```
Internal Consistency Reliability of the control model:
             f1        f2        f3        f4        y1     total
alpha 0.6627878 0.7443969 0.8027798 0.7979209 0.8138246 0.8639629
omega 0.6374891 0.7744233 0.8275411 0.8024112 0.8423732 0.8789794
```

```
Convergent validity of the test model:
              f1        f2        f3        f4        y1     total
AVE    0.4647085 0.6779937 0.6560743 0.6017762 0.6079569 0.5789777
```

```
Convergent validity of the control model:
              f1        f2        f3        f4        y1     total
AVE    0.4785476 0.5290111 0.6155678 0.5774889 0.6100084 0.5706460
```

APPENDIX VI: STRUCTURAL MODEL SYNTAX OF THE MODELS

Regression test group:

```
myModel2b <-'
f1 =~ exp1 + exp2 + exp3 + exp4
f2 =~ tru2 + tru3
f3 =~ sat1 + sat2 + sat3
f4 =~ abl2 + abl3 + abl4
y1 =~ bbl1 + bbl2 + bbl3 + bbl4
gender =~ x1
frequency =~ x2

#regressions
f2 ~ b*f1
f3 ~ d*f1
y1 ~ a*f1 + c*f2 + e*f3 + f*f4 + (c*f2)*(f*f4) + (e*f)*(f*f4)
y1 ~ g*gender + h*frequency

Moderationtrust := (c*f)
Moderationsatisfaction := (e*f)
Indirect effect := b*(c*f) + d*(e*f)
totaleffectf1 := a + b*(c*f) + d*(e*f)'
```

Regression control group:

```
myModelC2 <-'

#measurement model control group
f1 =~ cexp1 + cexp2
f2 =~ ctru1 + ctru2 + ctru3
f3 =~ csat1 + csat2 + csat4
f4 =~ cabl2 + cabl3 + cabl4
y1 =~ cbbl1 + cbbl2 + cbbl4
gender =~ x1
```

```
frequency =~ x2

#regressions
f2 ~ b*f1
f3 ~ d*f1
y1 ~ a*f1 + c*f2 + e*f3 + f*f4 + (c*f2)*(f*f4) + (e*f)*(f3*f4)
y1 ~ g*gender + h*frequency

Moderationtrust := (c*f)
Moderationsatisfaction := (e*f)
totaleffectf1 := a + b*(c*f) + d*(e*f)'
```