Consumer Preferences for Attributes of Livestream Shopping:
A Study of Generation Z

Aixilawei Aierken

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By: Aixilawei Aierken

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Signed by the final examining committee:

Bianca Grohmann   Chair
Chair's name

Onur Bodur   Examiner
Examiner's name

B. Kemal Buyukkurt   Supervisor
Supervisor's name

Approved by   Onur Bodur
                            Chair of Department or Graduate Program Director

8/23/2022   Kathleen Boies
                            Dean of Faculty

Abstract

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Aixilawei Aierken

Retailing is experiencing critical innovations in many areas. Livestream shopping (LS) is one of these innovations that combines shopping and social media. Experts predict LS to capture considerable share of retail sales rapidly as it has already done in China. This study reports the results of two surveys involving the relative importance of attributes of LS sites for generation Z because they are likely to be included in the early target segments. The first survey involves an application of the Case 2 Best-Worst Scaling (BWS2) (MaxDiff) to measure the relative attractiveness (utility) of LS attributes and their levels on an interval scale. Both the modeling approach based on random utility theory and the so called "counting approach" are used to analyze the BWS2 data to derive importance scales. They can be used as a guideline in the design of LS sites for generation Z. The results also suggest gender differences in perceived relative importance. These differences can be instrumental in differentiated market targeting. The second survey deals with the general shopping styles of generation Z consumers who participated in the first survey. It is hypothesized that general shopping styles will affect preferences for various attributes of LS sites. A factor analysis of the collected data suggests nine shopping styles with mean factor score differences for genders in four factors. The factors with higher mean factor scores for females help interpret the higher importance of a subset of the LS attributes for females. Limitations and future research directions are discussed.

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Unknown future beckons, and I will go ahead bravely.

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Introduction

  Online retailing has been evolving rapidly over the last decade and it is expected to go through major innovations in the near future (Fiedler et al., 2020; Grewal et al., 2017; Inman & Nikolova, 2017; Roggeveen & Sethuraman, 2020; Straw & Toriello, 2021). Advances in digital technology, increasing use of mobile devices globally and participation in social media by consumers, and the major shift in consumer shopping from "brick-and-mortar" stores to online shopping due to Covid 19 pandemic have contributed to the dramatic changes in the retail sector. Advances such as increasing availability of chat lines for consumers and recommendation agents, digital product assortment catalogs, availability of mobile brand and store apps, robotic shopping assistants, voice command technology etc. are only a fraction of the advances that facilitate consumers' decision making (Roggeween & Sethuraman, 2020). Roggeween and Sethuraman (2020) present an extensive catalog of 40 customer-interfacing retail technologies to enhance consumer search and shopping. Many of these technologies aid consumer decision making.

  Online retail industry witnessed other major advances in enhancing consumers' online experiences (Lemon & Vehoef, 2016; Puccinelli et al., 2009; Verhoef et al., 2009). The main objective of improving consumers' online experiences is to build and sustain consumer online engagement (Baldus et al., 2015; Barger et al., 2016; Brodie et al.,2011; Dessart et al., 2016; Hollebeek et al., 2014; Hughes et al., 2019; Martinek, 2021; Vivek et al., 2012). These improvements include the design and visual presentation of product assortments (Kahn, 2017), dynamic presentations (Roggeveen et al., 2015), augmented reality and 3D technologies (Cook et al., 2020) and potential developments of immersive technologies like metaverse (Elmasry et al., June 2022). Livestream online shopping is another recent and important example of a form of retailing that emphasizes enhancing consumer experience and engagement.

Literature Review

Livestream Shopping (LS)

Livestream Shopping (LS) is a relatively new form of live online shopping utilizing real time interaction of consumers with online retail outlets and their hosts (also called streamers) on social media. Consumers can access a live stream shopping session on social media, view product presentations and demonstrations by a host, ask questions, leave reviews, communicate with the host or chat with one another, and buy products at the LOS site if they decide to do so. It is a modern and revised version of TV shopping with the critical exception that it takes place on social media with extensive real-time interaction between the host and the viewers and interaction among the viewers. It blends social interaction, entertainment, promotion and instant purchase. This allows for a personal and engaging shopping experience since the viewers have the opportunity to participate and request explanations and express opinions and emotions regarding the products or services the host is presenting. In many LS outlets knowledge and experience of the streamer helps viewers learn about products/services, their attributes and unique features. Moreover, the social interaction can be extremely entertaining when it is led by an experienced streamer. Streamers can make on-the-spot promotions to sustain engagement. Live demonstrations and display of products in LS outlets seem to be more effective than online pictures on the web making the LS presentations more authentic. Streamers themselves can be celebrities or they may invite celebrities occasionally to expand their fan base. This, in turn may increase the credibility, trustworthiness and entertainment value of the presentations depending on the background of the streamers or their celebrity guests.

LS History and Expectations

LS as described just above started in China in 2016 with the introduction of Chinese shopping platform Taobao by the internet giant Alibaba (Alibaba Group, 2021; McKinsey Digital, 2021). This new retail platform demonstrated in China sales of three billion dollars to 171 billion dollars in an explosion over a short period from 2017 to 2020. Forecasters expect Chinese livestream sales to top $ 423 billion by the end of 2022 (McKinsey Digital, 2021). The evolution of livestream shopping into an innovative sales channel attracted the attention of entrepreneurs and marketers around the globe (McKinsey Digital, 2021). Social media platforms like Amazon Live, YouTube, TalkShopLive, Facebook Live, Instagram, Shopify, Twitch, and TikTok, and companies such as Bloomingdale's, Nordstrom, Walmart, Sephora, Mode Operandi, and many others (Koetsier, 2022; Lee, 2021) adapted this immersive and interactive channel type in North America reflecting their positive business expectations regarding the future of LS.

Despite the increasing popularity of LS in North America and in other countries besides China, a literature review of the related stream of research did not reveal any guidelines for the design of effective LS outlets. As practitioners begin to invest in this special form of online shopping, they will need information regarding the preferences of target consumers for different attributes of LS reminiscent of the concerns in conjoint analysis for the design of products and services (Carroll & Green 1995; Green & Rao 1971).

Objectives and Conceptual Framework of the Study

Figure 1 summarizes the conceptual framework of the thesis. Within this framework, the major objective of this study is to assess the relative attractiveness (importance) of various LS attributes for Generation Z. The study focuses on generation Z since it is already one of the major targets for LS. Almost all members of 15–24-year-olds (97.9 %) have smartphones in Canada (Statistics Canada, 2021) and 90% of the same cohort report that they shop online. Mobile phones are the digital devices of choice for 75 % of generation Z (Cheung et al., 2017) to be in contact with social media platforms where LS outlets are available. When they are asked to report what they do with their free time, 74 % of generation Z mention they spend time online (Cheung et al., 2017).

A secondary objective of this thesis is to learn about the shopping styles (Sproles & Kendall, 1986) of generation Z and the differences in shopping styles across genders in that generation to interpret the findings regarding the relative attractiveness of LS attributes. It is theorized that general shopping styles of generation Z are related to the perceived relative attractiveness of LS attributes. This study repeats the original study by Sproles and Kendall (1986) since some attempts to replicate their original study in different countries did not confirm the factor structure they suggested: there were some additional and missing factors (Bakewell & Mitchell, 2006; Lysonski et al.,1996; Michell & Walsh, 2004; Walsh & Mitchell, 2000). Furthermore, considerable time has elapsed since the original study and new forms of shopping emerged to which consumers may have adapted.

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┌─────────────────┐        ┌─────────────────┐        ┌─────────────────┐
│ Shopping Style, │        │ Perceived       │        │                 │
│ Gender          │───────▶│ Relative        │───────▶│ Engagement with │
│ Differences     │        │ Importance of   │        │ LS Outlet       │
│                 │        │ Attributes of LS│        │                 │
│                 │        │ Outlets         │        │                 │
└─────────────────┘        └─────────────────┘        └─────────────────┘
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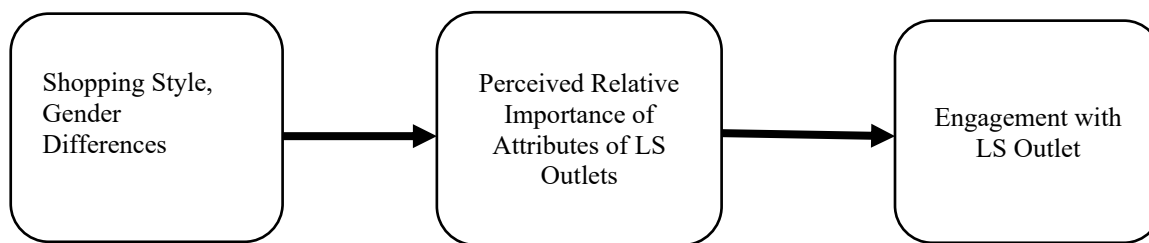
Figure 1: Conceptual Framework of the Study

Attributes of LS

The following section discusses the compilation of a list of attributes of LS outlets that Generation Z consumers may pay attention to in their decisions to engage with an LS outlet. A hypothesis follows each attribute. The list of attributes is based on several unstructured interviews with generation Z consumers who are familiar with (heard about or visited) or shopped (made a purchase) at a LS outlet. Three of the interviewees had experiences with Taobao live streaming. LS outlets on Amazon Live were reviewed to identify the product categories, brands, and uniqueness of the products marketed, types of interaction involved at the

LS outlet, and the characteristics of the hosts (streamers) that may be relevant to the consumers. Certain general characteristics and interests of generation Z mentioned in the literature guided these LS outlet reviews to identify the LS outlet attributes that may be relevant to generation Z. Since the objective was to identify the LS attributes that may motivate engagement with a LS outlet, an operational definition of the construct of consumer online engagement was needed.

Engagement with a LS outlet

The literature regarding online consumer engagement is rich in terms of various construct definitions and their operationalizations (Baldus et al., 2015; Barger et al.,2016; Brodie et al.,2011; Dessart et al., 2016; Hollebeek et al., 2014; Hughes et al., 2019; Martinek, 2021; Vivek et al.,2012). As reviewed in the mentioned articles the conceptual definition and measurement of consumer engagement varies considerably depending on the consumers' context and the focus of engagement (e.g., a brand, product type, blog, web site, brand community, online social platform, or influencer). Most definitions agree that, as a psychological state, engagement involves cognitive, affective, and behavioral relationships with the focus of engagement. Following the definitions suggested by Dessart, Veloutsou and Morgan-Thomas (2015, p.12) based on their extensive literature review, in this study affective dimension of engagement involves emotions (excitement, interest, enjoyment, fun, entertainment) experienced by a consumer as a result of relationships with a LS outlet. Cognitive dimension of engagement includes thoughts and mental states (attention, concentration, immersion, opinions) associated with the LS outlet. Behavioral dimension involves activities associated with the LS (searching for and attending a LS presentation, learning, various types of interaction at the LS site such as posting comments, asking questions to the host and other viewers, purchasing a product, etc.) As discussed in the data collection section, the operational definition of engagement in this study focused more on the behavioral dimension.

Since the definition of engagement depends on the context and focus of engagement (Dessart et al. 2015), a special characteristic of a LS outlet needs to be mentioned. A LS outlet provides opportunity for a purchase as an online store. It also provides opportunity for various forms of interaction as a social media site. Therefore, certain attributes of online and brick-and-mortar stores (Burke, 2002; Hansen & Deutscher, 1977-1978; Ganesh et al., 2010; Kelly & Stephenson, 1967; Porat & Tractinsky, 2012; Stephenson, 1969) that motivate patronage such as prices, product assortment, and brands become relevant in the context of engagement with a LS outlet. Furthermore, characteristics of the host (streamer) and the guests as influencers play a major role in the engagement with a LS outlet. Hence, engagement with a LS outlet is a combination of engagement with the host, an online store, and a social media site.

Table 1 on page 16 presents the list of attributes of LS sites expected to be important for generation Z. Admittedly the list could include many more attributes. As discussed in the following sections Best-Worst Scaling rather than methods such are Likert ratings was used to generate a reliable scale of generation Z preferences for the attributes of LS sites and avoid some potential biases of rating scales such as "end-piling" of ratings and lack of invariance of measurement. To achieve this end, the number of attributes and their levels were limited such that the total number of LS profiles to be presented to the respondents of the related surveys were manageable. The data collection chapter below explains how a discrete choice experimental design created combinations of the attributes and their levels as profiles of LS sites.

<center>**Hypotheses of the Study**</center>

Prices at a LS Site

Expected prices to be paid at a store is a critical attribute associated with a store choice. Patronage for stores with lower prices, keeping other attributes constant, increases with lower prices (Burke, 2002; Ganesh et al., 2010; Hansen & Deutscher, 1977-1978; Kelly & Stephenson, 1967; Porat & Tractinsky ,2012; Stephenson, 1969). Similarly, a global survey of 15,600 members of generation Z between ages 13 and 21, 65 % indicated they want to get real value for their money with discounts, coupons and a rewards program (Cheung et al. 2017). In an international Lifestyles Survey conducted in 2020 by Euromonitor, close to 40 % of generation Z respondents mentioned that they like to find bargains, and they are willing to trade down for more value by seeking private label/low-cost products (20%). An overwhelming portion of generation Z are students with lower levels of average income than other generations. Moreover, many of them were unemployed during the Covid 19 pandemic. Both factors contribute to their price sensitivity and value seeking. Therefore, it is hypothesized that

H1: Lower prices are more important to generation Z consumers than no price advantages for engagement with a LS site.

Host Characteristics

The host (streamer) at a LS site is an influencer who makes presentations and demonstrations of products, interacts with the viewers, informs the viewers about products and their attributes, entertains the viewers and tries to persuade them to make purchases in a social media atmosphere. The hosts at a LS site assume the roles of opinion leader, salesperson, spokesperson, mediator, entertainer and expert (Zhang et al., 2022). Therefore, many characteristics of influencers that enhance and sustain consumer engagement are relevant in this context. A review of the related literature suggests that expertise (knowledge, credibility) and trustworthiness of influencers (spokespeople, LS hosts) are critical in building and sustaining consumer engagement (Farrell et al.,2022; Hughes et al., 2019; Liu & Kim, 2021; Ohanian, 1990; Zhang et al. 2022). Authenticity is a third host characteristic especially important for generation Z (Cheung et al., 2017; Demirsoy, 2017). As brand authenticity increases brand engagement (Morhart et al. 2015), authenticity of a LS site host is likely to increase consumer engagement with that site. A third key characteristic of successful LS hosts is entertaining the viewers (Farrell et al., 2022; Liu & Kim, 2021) which attracts the recreational shoppers (Kang et al., 2014) as well as consumers with other motives. Entertainment keeps viewers longer at the site along with immersive interaction. Based on these findings in the literature, three key host characteristics are included in this research: how knowledgeable (expert), entertaining and authentic the host is. The literature does not suggest any hypotheses with regard to the relative importance of each of these characteristics in building and sustaining consumer engagement. Post-hoc hypothesis testing may suggest further hypotheses for follow up studies. However, having all three characteristics rather than only one or two of them is expected to be more effective for consumer engagement. So, the following hypotheses are stated:

H2A: Hosts who are knowledgeable, entertaining and authentic are more important to

generation Z consumers than hosts are knowledgeable for engagement with a LS site.

H2B: Hosts who are knowledgeable, entertaining and authentic are more important to generation Z consumers than hosts are entertaining for engagement with a LS site.

A third hypothesis emphasizes the importance of authenticity for Generation Z.

H2C: Hosts who are knowledgeable, entertaining and authentic are more important to generation Z consumers than hosts are entertaining and knowledgeable for engagement with a LS site.

Interactivity

A key difference of LS in comparison to shopping at common brand and company web sites is the degree of interactivity enabled by the social media. Posting of messages by the viewers at the social media site, asking questions to the staff and/or the host, text responses by the staff, live responses by the host in real time increase entertainment value of the attended session. Moreover, they enable the streamers (influencers) to start and build parasocial relationships with the consumers (Horton & Wohl, 1956). According to parasocial relationship theory (Horton & Wohl, 1956) individuals may feel a personal connection with mass media personalities that they have not met but develop feelings of affinity towards them and express strong emotional connections with them (Farrell et al., 2022). Social media offers online direct communication tools such as voice, video, and texting for both the host and the staff at a LS site and the viewers. Influencers may share personal details about themselves and opinions about products and daily events which may make consumers feel "…as if they have acquired intimate information" (Farrell et al., 2022, p.38). As a result, they may feel more intimate with the influencer (Perse & Rubin, 1989) and the site that the influencer is affiliated with. Both the entertainment value and the parasocial relationship enhance engagement with the site and the host. As the variety and number of effectively used interactive tools increases, perceived importance of interactivity in engagement with a LS site is likely to increase. Three increasing levels of interactivity during live presentations are examined in this study: (1) consumers may post messages at the LS site, (2) consumers may post messages at the LS site and the staff at the LS site responds to selected messages, and (3) consumers may post messages at the LS site, staff at the LS site responds to selected messages, and the host responds to selected messages. A comparison of the perceived importance of each level of interactivity and no interactivity against the third level involving all three types of interaction will give an idea regarding the perceived importance of the host and the remaining interaction tools simultaneously against other mentioned alternatives. Therefore, it is hypothesized that

H3A: Interactivity involving posting messages by consumers, viewing text responses to selected consumer messages by the staff and observing live audio-visual responses by the host to selected messages is more important for generation Z than no interaction for engagement with a LS site.

H3B: Interactivity involving posting messages by themselves, viewing text responses to selected consumer messages by the staff and observing live audio-visual responses by the host to selected messages more is more important for generation Z than only posting

messages by themselves for engagement with a LS site.

H3C: Interactivity involving posting messages by themselves, viewing text responses to selected consumer messages by the staff and observing live audio-visual responses by the host to selected messages more is more important for generation Z than only posting messages by themselves or by the staff for engagement with a LS site.

Marketed Brands and Their Uniqueness

It is possible to categorize the product assortment at a LS site into four groups by considering how established and unique the marketed brands are. The majority of the offered brands may be established (have been in the market for a while and built loyalty) or recently introduced brands trying to build relationships with a target market.

Additionally, the majority of the items in the product assortment may be unique designs or designs that are available in other online or brick-and-mortar stores. When these two factors with two levels each are crossed, the resultant categorization involves four possibilities: (1) established brands with designs available elsewhere, (2) established brands with new unique designs, (3) new brands with designs that consumers can find elsewhere, (4) new brands with unique designs.

Generation Z seems to be interested more in buying unique products that will give them the best value rather than being very loyal to established brands (Bump, 2021; Finneman et al., 2021; Hanbury, 2019). "Being unique – and balancing that with saving money – is a defining trait of this generation." (Hanbury, 2019). Finneman et al. (2021) write "…Gen Z doesn't think of luxury as a name brand that they want to slap onto their bag or shirt and wear as a badge. They're really looking for unique items that set them apart…And if they find it from a luxury brand, then they're absolutely willing to pay for it." However, generation Z consumers are likely to search for authentic, new and unique brands or brands with unique designs if they can match their values with the values of the brand/and or LS site rather than focus exclusively on established brands as potential badges (Bump, 2021; Finneman et al., 2021; Hanbury, 2019). Given these observations, the following hypotheses are stated:

H4A: New brands and unique designs are more important to generation Z consumers for engagement with a LS site than known brands and familiar designs.

H4B: New brands and unique designs are more important to generation Z consumers for engagement with a LS site than new brands and familiar designs.

H4C: Unique designs are more important to generation Z consumers for engagement with a LS site than designs marketed elsewhere.

Product Assortment

Product assortment affects store choice and consumer patronage (Briesch et al., 2009; Burke, 2002; Ganesh et al., 2010; Hansen & Deutscher, 1977-1978; Kelly & Stephenson, 1967; Stephenson, 1969). Similarly, product categories marketed by a LS site are likely to affect consumer engagement with that site.

To investigate the consumer preferences for a specific product category in relation to other

product categories in LS shopping, this study focuses on a sample of four product categories currently popular at LS sites. The sample includes both utilitarian and hedonic product categories and appeals to both genders. Extant literature suggests that whether the related product category is hedonic or utilitarian (Dhar & Wertenbroch, 2000; Hirshman & Holbrook, 1982) is a moderator of consumer shopping behaviour (Kushwaha & Shankar, 2013). Gender, too, plays a key moderating role in consumer online shopping (Kanwal et al., 2022). The sample of product categories includes (1) beauty products and cosmetics, (2) clothing and fashion items, (3) food and cooking, and (4) consumer electronics.

Hedonic products involve emotional arousal, relate to esthetics, multisensory imagination and fantasy, (Hirschman & Holbrook, 1982). They provide fun, pleasure, excitement whereas utilitarian products are more functional and instrumental (Dhar & Wertenbroch, 2000). In the current study, product categories (1), (2) and (3) may be qualified as involving hedonic qualities but consumer electronics may be classified as involving more utilitarian qualities.

Surveys of LS events suggest that shares of LS events for apparel and fashion, beauty, and consumer electronics are 35.6 %, 7.6 % and 4.6 %, respectively (Arora, 2021). It is interesting that majority of the LS events are related to product categories such as apparel and fashion, beauty products and cosmetics that may involve hedonic qualities. Assuming that the market response as noted reflects consumer preferences in LS shopping, the following hypotheses are stated:

H5A: Clothing and fashion items more important to generation Z consumers for engagement with a LS site than consumer electronics.

H5B: Beauty products and cosmetics are more important to generation Z consumers for engagement with a LS site than consumer electronics.

Gender differences as well as whether the generation Z consumers perceive the product category marketed at a LS site more hedonic or utilitarian are likely to moderate which product category is perceived to be more attractive for engagement by generation Z. Gender differences in consumer behavior has been a topic of managerial and theoretical concern for decades (Myers-Levy & Loken, 2015). Consumers' shopping styles (Bakewell & Mitchell, 2006; Kanwal et al., 2022; Mitchell & Walsh, 2004), choice of products (Girard et al., 2003; Kanwal et al., 2022) and preferences in different channels of distribution involve gender differences (Dittmar et al., 2004; Eastlick & Feinberg, 1994; Garbarino & Strahilevitz, 2004; Girard et al., 2003; Lee et al., 2013; Nysveen et al., 2005).

Four major theories seem to provide potential explanations for the observed gender related differences in consumer behavior (Myers-Levy & Loken, 2015). Social-psychological theory attributes gender differences to physical differences and the related different roles that males and females adopt in society. Evolutionary theory focuses on adaptive behaviors that males and females have developed over time to deal with environmental demands. Medical-biological theories focus on differences in hormonal and brain related activities of the genders. Finally, selectivity theory emphasizes differences in information processing (Meyers-Levy & Maheswaran, 1991).

As underlined by Myers-Levy and Loken (2015) these theories provide potential explanations for gender differences in a complementary rather than competitive manner. Both genders may prefer brands with identities that match their gender identity (Grohmann, 2009).

Similarly, both genders may prefer LS sites that match their social roles related to their gender identities. As a result, females may prefer beauty products and cosmetics to electronics in building engagement with a LS site. Males, on the other hand, may focus on LS sites that offer electronics rather than beauty products and cosmetics since the male persona in a society does not involve interest in cosmetics and beauty products related to female persona but involves male image that has evolved in many societies conveying familiarity with electronics and products with advanced technology. From an evolutionary theory perspective, beauty products, cosmetics, attractive clothing and fashion designs may increase female consumers' chances of looking more attractive to a male with resources (Hill et al., 2012) and compete better with other females during periods of evolution (Durante et al., 2011).

Kanwal et al. (2022, p. 38) provide a review of nine published articles and summarize gender-specific product preferences for online shopping. Males prefer shopping for entertainment tickets, intangible and digitized offerings, books and computers, mobile phones, television, online purchase of cooked food, and sporting goods. Females, on the other hand, prefer clothing and perfumes, apparel and jewelry, fashion and beauty products, online grocery shopping, food shopping for cooking ingredients.

Given the above findings reported in the literature, the following hypotheses as are formulated regarding gender differences in Generation Z:

H6A: Beauty products and cosmetics are more important to female generation Z consumers than male generation Z consumers for engagement with a LS site.

H6B: Clothing and fashion products are more important to female generation Z consumers than male generation Z consumers for engagement with a LS site.

H6C: Beauty products and cosmetics are more important to female generation Z consumers than clothing and fashion items are to male generation Z consumers for engagement with a LS site.

H6D: Beauty products and cosmetics are more important to female generation Z consumers than electronics for engagement with a LS site.

H6E: Clothing and fashion products are more important to female generation Z consumers than electronics for engagement with a LS site.

H7A: Electronics are more important to male generation Z consumers than female generation Z consumers for engagement with a LS site.

H7B: Electronics are more important to male generation Z consumers than beauty products and cosmetics for engagement with a LS site.

As mentioned above in the section regarding the objectives of this study, a secondary objective of this thesis research is to supplement the interpretation of the hypothesis tests with information regarding the shopping styles of the same subjects of the study. For this purpose, a revised version of the survey instrument constructed originally by Sproles and Kendall (1986) was administered to the subjects. Previous attempts to replicate the findings reported by Sproles

and Kendal (1986) using confirmatory factor analysis suggested certain factors similar to their findings. However, there were also differences in the extracted factorial structure. Findings suggested some additional factors in different countries for different genders (Bakewell & Mitchell, 2006; Lysonski et al., 1996; Michell & Walsh, 2004; Walsh & Mitchell, 2000). This suggests lack of measurement invariance. Also, because a long time has passed since the reported studies, new shopping channels emerged on the web and social media became prominent, shopping styles of the young generation most likely have changed. Furthermore, assessing the psychometric properties of the shopping style questionnaire is not the primary objective of this thesis. Hence, this study does not involve any specific hypotheses regarding the factor structure of the collected shopping style data. An exploratory factor analysis is planned rather than a confirmatory one as discussed in the chapter on data analysis.

Best-Worst (Max-Diff) Scaling

Testing the hypotheses of the study regarding the relative attractiveness of the attributes of Livestream Shopping (LS) and understanding the patterns in the heterogeneity of such perceptions for segmentation purposes were carried out using Best-Worst Scaling (BWS) and its extensions within the Multinomial Logit (MNL) modeling framework. This section briefly reviews the fundamentals of BWS, its variants, questionnaire design and data collection issues for carrying out BWS in general. Also presented are the advantages of BWS over rating scales to justify the use of BWS in the present context. Details of the construction of a discrete choice design for BWS and the related questionnaire for this study are mentioned later in the chapter on Data Collection and Questionnaire design. Analysis of the collected BWS data, hypothesis testing regarding the relative attractiveness of attributes of LS and examination of the patterns of heterogeneity in consumer perceptions of the relative attractiveness scores are presented in the chapter on Data Analysis.

BWS is a widely used stated preference method (Louviere et al., 2000) that places individuals in hypothetical choice situations defined by controlled experiments. Its purpose is to measure individuals' preferences regarding (1) attributes, or (2) attributes and their levels, or (3) alternatives constructed in terms of attributes and their levels based on experimental design principles. The method is based on the assumption that individuals can identify the best and the worst (most important and least important, most attractive and least attractive, smallest and largest, etc.) out of a set of more than two options. The pair chosen as the "best" and "worst" are assumed to be perceived as the farthest apart and maximally different on an underlying common and latent continuum in comparison to other possible pairs (Auger et al., 2007; Louviere & Islam, 2008). Hence, the related model that was developed for "best-worst scaling" is also called "max-diff" model in the literature especially by those who use the commercial Sawtooth Software for BWS (Chrzan & Orme 2019; Cohen, 2003).

BWS can be considered as an extension of paired comparison (David, 1969; Thurstone, 1927) from two sets of objects with three or more alternatives (Jaeger et al., 2008). Instead of asking for the preferred alternative in a pair, BWS asks for additional information regarding the worst alternative as well as the best one in a choice set of more than two alternatives. This additional information for each choice set allows for the ranking of all choice items when the best and worst items are identified by respondents across different subsets of the choice items constructed following certain experimental designs. Assume that the total set of choice items includes (A, B, C, D, E, F) and a subset (A, C, D, F) are presented to the subject and the subject identifies A as the best and C as the worst. This implies the A > C, A > D, A > F, D > C, and F > C, using > to indicate "preferred to". Only the preference relationship between D and F is not clear. However, repeating the BWS task systematically with other subsets of the choice items allows for a complete ranking of the whole set of items clarifying the preference relationship between items like B and C in the example (Cohen, 2003).

Various experimental designs are suggested in the literature for constructing BWS preference tasks. If the focus is on scaling of different attributes (also called "object case" or Case 1), a two-level orthogonal main effects design (OMED) or a balanced incomplete block design (BIBD) (Auger, et al., 2007) can be used. OMED can be easily extended to K attributes with L_k levels each to construct BWS tasks for multiple attributes and their levels (also called "profile case" or Case 2). If the preference tasks involve multiple profiles of choice objects defined in terms of attribute levels (called "multiple profiles case" or Case 3) as in discrete

choice experiments (DCE), fractional factorial design/orthogonal arrays can be used to create profiles of objects. Next, the profiles are assigned to preference tasks using BIBD (Fogarty & Aizaki, 2018; Louviere et al., 2015). See Hensher, Rose and Green (2015) and Kuhfeldt (2005) for a further discussion of DCE designs. Kuhfeld (2005) shows how to construct experimental designs for choice tasks using SAS. Aizaki and Nishimura (2008) demonstrate how to use R language (R Core Team, 2021) for the design and analysis of choice experiments. Louviere, Pihlens and Carson (2010) present a discussion of issues in future applied research involving discrete choice experiments.

Theoretical properties of BWS are directly related to Luce's (1959) choice axiom and probabilistic choice model, and McFadden's (1974) Multinomial Logit model through a random utility conceptualization (Flynn & Marley, 2014; Louviere et al., 2015; Marley & Louviere, 2005). "Thus, best-worst choice data can be transformed to a probability scale when analyzed by multinomial logit" (Jaeger, et al., 2008). This theoretical connection between the properties of the BWS data and the multinomial logit model with its extensions such as latent class analysis, mixed logit analysis, generalized multinomial logit etc. (Sarrias & Daziano, 2017) allows for testing specific hypotheses and examination of heterogeneity in subjects' best-worst related judgments in stated preference tasks.

Case 2 BWS

Since the hypotheses of the study involve both the relative attractiveness of attributes and their levels (see Table 1 on p. 16), for example, "price" attribute with levels "lower than other retail outlets" and "similar to other outlets") the data collection process and the subsequent statistical analysis of this study rely on modeling of Case 2 of BWS (Aizaki & Fogarty, 2019; Flynn & Marley, 2014; Louviere et al., 2015). In Case 2 BWS respondents review profiles of objects each of which present information about several attributes with experimentally chosen attribute levels and asked to choose the best and the worst attribute levels for the presented profile. Collecting the responses to a sequence of responses by the same respondent and analyzing such data reveal the preferences of the respondents regarding the attributes and their levels. Guidelines for constructing Case 2 BSW preference tasks with multiple profiles can be found in (Flynn et al., 2007; Hensher et al., 2015; Louviere et al., 2015). The details of data collection and the analysis of the collected data in the current study will be discussed in the chapters on Data Collection and Data Analysis below.

Modeling for Case 2 BWS

Discrete choice models (Hensher et al., 2015; Train, 2009) constitute the foundation to model BWS responses. For Case 2 BWS, three variants were suggested in the literature regarding the process in which respondents perceive utility in each attribute level and how they choose the best and the worst attribute levels. Assume that there are n attribute levels in a profile, and the subject chooses attribute level i as the best and attribute level j as the worst level. Using the notation in Aizaki and Fogarty (2019) and assuming that the utility of the best level is the negative of the worst level, the three variants of Case 2 BWS are as follows.

1) The Paired Model: It is assumed that the difference in utility between the best and the worst attribute levels is the maximum utility difference among all $n \, x \, n(-1)$ possible utility differences in a profile S. Using the conditional logit model and denoting the systematic

component of utility for level k as u_k (Aizaki & Fogarty, 2019; Flynn & Marley, 2014), probability of selecting level i as the best and level j as the worst from profile S is

$$\Pr(best = i, worst = j) = \frac{\exp{(u_i - u_j)}}{\sum_{p,q \subset S, p \neq q} \exp{(u_i - u_j)}}$$

2) The Marginal Model: This model assumes the respondent selects level i as the best from all n levels in a profile, and level j as the worst from all n levels in the same profile. The related conditional logit model is

$$\Pr(best = i, worst = j) = \frac{\exp{(u_i)}}{\sum_{p \subset S} \exp{(u_p)}} \frac{\exp{(-u_j)}}{\sum_{p \subset S} \exp{(-u_p)}}$$

3) The Marginal Sequential Model: This variant of Case 2 BWS changes one of the assumptions of the marginal model and asserts after the best level i is selected from profile S, the worst level j is selected from the remaining $(n - 1)$ levels. Hence, the associated conditional logit model is

$$\Pr(best = i, worst = j) = \frac{\exp{(u_i)}}{\sum_{p \subset S} \exp{(u_p)}} \frac{\exp{(u_j)}}{\sum_{p \subset S-i} \exp{(-u_p)}}$$

Given a data set involving the best-worst preferences of respondents following a proper experimental design the coefficients of the related conditional logit model can be estimated. These coefficients represent the respondents' preferences regarding attributes and/or levels depending on how the data are coded (Aizaki & Fogarty, 2019).

BWS as a data collection and modeling approach has been very popular in various areas such as marketing (Chrzan & Govashkina, 2006; Cohen 2003, 2009; Massey et al., 2015; Mueller et al., 2010; Parvin et al., 2016), economics (Guo & Shen, 2019), welfare economics (Louviere & Islam, 2008), cross cultural ethical beliefs (Auger et al., 2007), health care (Cheung et al., 2016; Flynn et al., 2007; Lanscar et al., 2013; Mühlbacher et al., 2016), food science (Millman et al., 2021), and social values (Lee et al., 2008). BWS is theoretically related to random utility models. This enables the use of multinomial logistic regression and its extensions in analyzing BWS data and test statistical hypotheses. In addition, BWS measures have clear advantages against popular alternatives such as rating scales as discussed later in more detail.

Data Collection

Two online surveys, Part 1 and Part 2, were conducted with the same respondents using Qualtrics survey platform. The participants of the study were students taking an introductory marketing course in the core business program at Concordia University. They participated in the study as a component of an introductory marketing course. Since the study focused on the perceptions and shopping styles of generation Z, a qualifying question in the survey determined the birth date of the respondents. The sample of respondents were all university students born in 1997 or later belonging to Generation Z.

Participants applied to a university web site to sign up for the surveys. Credits towards the completion of the course in marketing were given to those who completed both parts. 365 and 320 respondents participated in surveys Part 1 and Part 2, respectively. 240 of these respondents completed both Parts 1 and 2 with no missing data.

Each participant responded to Part 1 and Part 2 at least a week apart. Part 1 of the survey focused on measuring the relative attractiveness of various attributes of Live Stream Online Shopping (LS). In Part 2, the survey focused on measuring the shopping styles of the respondents' using items from a measurement scale that was developed by Sproles and Kendall (1986). Because it is possible that the participants' responses to Part 2 might be affected by the recall of the responses regarding the relative attractiveness of the attributes of LS in Part 1, Part 2 was administered at least a week after Part 1 for each subject. Thus, possible recall of the responses to Part 1 was at least partially reduced and subjects would be less inclined to give responses in Part 2 just to appear consistent with their responses in Part 1.

Both parts of the survey started with an introduction section that presented information about the nature and purpose of the survey and a consent form that described the steps in the administration of the survey, risks and benefits of the survey, and strict confidentiality of the information provided by the subject. This section emphasized that the subjects did not have to participate in the study, could stop any time without any negative consequences, if they responded to any questions on the survey, they could ask the information not to be used, and contact the researcher by email or phone call if there were any questions associated with the survey. Finally, the respondents signed a consent form indicating that they agree to participate in the survey under the conditions described.

Part 1: *Best-Worst Scaling Case 2 (BWS2)*

Appendix 1 presents the complete questionnaire for Part 1 of the survey. The introduction section to Part 1 of the study focused on reviewing the nature of Live Stream Online Shopping (LS), its emergence and increasing popularity in China and North America, types of interaction involved in LS and the product categories currently marketed through LS. Respondents viewed YouTube videos titled "The Evolution of Taobao Live" (Alibaba Group, 2021) and "What is Live Video Shopping" (Bambuser, 2021). Each presentation was limited to approximately the first 3.5 minutes of the available video. Participants also saw images of LS outlets about marketing of product categories involving cosmetics, fashion, cooking and technology. The major objective of this section on LS was to ensure that the subjects were familiar with the history, nature, attributes and increasing popularity of LS. Although the majority of the generation Z participants were in general expected to be aware of the developments in this form of retailing, a review would be helpful in establishing a uniform understanding of LS across the sample.

Next, the questionnaire presented a definition of engagement as "viewing the presentations and demonstrations by a host at an LS outlet, and possibly interacting by texting and/or calling the site staff and the host on the phone, and buying product/service." It was also noted that previous research suggested that consumers' likelihood of engaging with an LS may be affected by some attributes of the outlet. Some of the attributes were listed as (1) the characteristics of the host, (2) prices at the site, (3) nature of interactivity offered at the site, (4) categories of product marketed, and (5) marketed brands, models and their uniqueness.

The remaining section of Part 1 questionnaire was related to the measurement of relative attractiveness of various attributes of Live Stream Shopping (LS) based on Best-Worst Scaling Case 2 (BWS2) (Aizaki & Fogarty, 2019; Flynn et al., 2007; Louviere et al., 2015). For this purpose, first, a table of LS attributes and their levels were constructed (Table 1) where the rows are the attributes and the columns are their levels. Unstructured personal interviews of users of LS, user remarks at various LS web sites, video reviews of what LS is and literature review as presented above guided the selection of the final set of attributes and their levels. As presented in Table 1 there were five attributes four of which had four levels and one attribute had only to levels. For example, the attribute "host" has four levels and "price" has two levels. Level 2 for host is "entertaining" and Level 1 for price is "lower than other outlets".

Profiles of LS outlets were generated by using only one level of each attribute and following orthogonal main effects designs (OMED) (Aizaki, 2019). The use of OMED is similar to the use of orthogonal experimental designs in conjoint analysis to construct product or service profiles (Carroll & Green 1995; Green & Rao 1971). Table 2 presents the design matrix for the current study where the columns are attributes and the rows are different LS profiles. Each row (LS profile) appears as a question in the BWS2 questionnaire. Note that there are 16 rows in the design matrix corresponding to 16 BWS2 questions in Part 1 of the survey. The sequence of the rows of the design matrix was randomized to reduce any potential order effects in the responses to the questionnaire.

Another important feature of the OMED in Table 2 is that the levels for each attribute are balanced in the sense that each level appears an equal number of times across the whole design. For example, each level of the attributes with four levels across 16 rows of the design matrix appears four times in the design. For the attribute with two levels, each attribute appears eight times in the design.

Figure 2 displays an example of a BWS2 question. The example shows an LS outlet with an entertaining host where no interaction with the site is possible, prices are lower than other retail outlets, consumer electronics are marketed, the offered brands are new but their designs are similar to designs offered elsewhere. In this hypothetical response, the respondent chose "price lower than competition" as the **best** and "new brands are marketed with similar designs elsewhere" as the **worst** attribute of the described LS outlet indicating two attribute levels that are furthest apart from each other. 16 such questions appeared in the questionnaire following the design matrix in Table 2. Please see Appendix 1 for the complete questionnaire.

Table 1. Experimental Design Factors and Their Levels for BWS2 Questions

Factor (Attribute)	Levels of Factor			
	1	2	3	4
Host	Knowledgeable	Entertaining (*)	Knowledgeable, Entertaining	Knowledgeable, Entertaining, Authentic
Price	Lower than other retail outlets	Similar to other retail outlets (*)		
Interactivity	No Interaction (*)	Consumers can text	Consumers and Staff text each other	Consumers can text, host can respond live
Marketed Products	Beauty Products, Cosmetics	Clothing, Fashion	Food, Cooking Related (*)	Consumer Electronics
Brand, Uniqueness of Design	Known Brands, Marketed Elsewhere (*)	Known Brands, Unique Design	New Brands, Similar design marketed elsewhere	New Brands, Unique Designs

(*) Reference levels in different types of BWS2 models.

Table 2. Design Matrix for BWS2 Questions

	Level Number of Each Factor Used in Each BWS2 Question				
Survey Question	Host	Prices	Interactivity	Products	Brand Uniqueness
1	2	2	4	3	1
2	3	2	2	4	1
3	4	2	1	3	2
4	4	2	2	1	3
5	1	2	4	2	3
6	4	1	4	4	4
7	1	1	2	3	4
8	4	1	3	2	1
9	2	1	1	4	3
10	1	2	3	4	2
11	2	2	3	1	4
12	2	1	2	2	2
13	3	1	3	3	3
14	3	1	4	1	2
15	3	2	1	2	4
16	1	1	1	1	1

Figure 2. Example of a Best-Worst Scaling Choice in Part 1

A Live Stream Online Shopping outlet is described below. Please read the description carefully. Indicate which of these attributes would be the BEST and which one would be the WORST attribute for you if you considered engaging with this site.

Best Attribute		Worst Attribute
○	HOST: entertaining	○
●	PRICES: lower than competition	○
○	INTERACTION: Watch, buy.	○
○	PRODUCTS: consumer electronics	○
○	BRANDS: new brands, similar designs elsewhere	●

Part 2 of the study employs a measurement scale constructed by Sproles and Kendall (1986) to examine the different shopping styles of Generation Z. A few of the questions used in Part 2 involve slight changes in wording as compared to the original questionnaire. For example, in the original questionnaire constructed by Sproles and Kendall (1986), they used such wording as "Going shopping is one of the enjoyable activities of my life", "Shopping the stores wastes my time". Since the purpose of the current study is to examine shopping style in general, we decided to rephrase them as "Shopping is one of the enjoyable activities of my life", "Shopping wastes my time".

Based on a factor analysis, Sproles and Kendal (1986) identified eight major categories of shopping style. Part 2 questionnaire included four items related to each of the eight shopping styles as suggested in by Sproles and Kendal (1986). The eight categories of consumer shopping styles are:

1. "Perfectionist, high-quality conscious consumer": consumers with this cognitive awareness carefully and systematically compare the quality of products and do not easily get satisfaction, they carefully compare the attributes of products to search for the best quality products.
2. "Brand conscious and "price equals quality" consumer": consumers with this orientation are "brand conscious" and value brands. They tend to buy international brands and well-known brands, prefer specialty stores and boutiques, and prefer products that are popular and have a lot of advertising.
3. "Novelty and fashion-conscious consumer": consumers with this orientation derive excitement and pleasure from the pursuit of novelty, they follow trends and seek diversity.
4. "Recreational and hedonistic consumer": consumers with this orientation view shopping as fun and shopping for recreation.
5. "Price conscious and "value for money" consumer": consumers with this orientation are very price sensitive and value for money.
6. "Impulsive and careless consumer": consumers with this orientation buy without a plan, are more affected by the situation and don't care how much they spend or whether they make the best deal and are prone to impulsive buying.
7. "Confused by over choice consumer": consumers with this orientation find it difficult to make decisions because there are too many brands, too many stores, too much information about the product, and they are overwhelmed by the amount of information they receive.
8. "Habitual and brand-loyal consumer": consumers with this orientation usually have favorite brands and stores, and usually make habitual purchases and go to familiar stores. This is a very typical style of consumer shopping decision making.

Part 2 questionnaire included 29 of the original 40 Likert-scale items studied by Sproles and Kendall (1986) to reduce the length of the questionnaire so that the response rate for Part 2 would not be affected. For this purpose, items with relatively low loadings in the Sproles and Kendal (1986) were eliminated while maintaining four items for each factor (shopping style). Respondents were asked to indicate their degree of agreement or disagreement with each item on a 1 (strongly disagree) to 7 (strongly agree) scale. See Appendix 2 for Part 2 questionnaire.

Table 3. Consumer Shopping Style Characteristics

Factor 1 — Perfectionistic, High-Quality Conscious Consumer
1. Getting very good quality is very important to me.
2. When it comes to purchasing products, I try to get the very best or perfect choice.
3. In general, I usually try to buy the best overall quality.
4. My standards and expectations for products I buy are very high.

Factor 2 — Brand Conscious, "Price Equals Quality" Consumer
5. The well-known national brands are best for me.
6. The more expensive brands are usually my choices.
7. High quality department and specialty stores offer me the best products.
8. I prefer buying the best-selling brands.

Factor 3 — Novelty-Fashion Conscious Consumer
9. I usually have one or more outfits of the very newest style.
10. I keep my wardrobe up-to-date with the changing fashions.
11. Fashionable, attractive styling is very important to me.
12. To get variety, I shop different stores and choose different brands

Factor 4 — Recreational, Hedonistic Consumer
13. Shopping is not a pleasant activity to me.
14. Shopping is one of the enjoyable activities of my life.
15. Shopping wastes my time.
16. I enjoy shopping just for the fun of it.

Factor 5 — Price Conscious, "Value for Money" Consumer
17. I buy as much as possible at sale prices.
18. The lower price products are usually my choice.
19. I look carefully to find the best value for the money.

Factor 6 — Impulsive, Careless Consumer
20. I should plan my shopping more carefully than I do.
21. I am impulsive when purchasing.
22. Often I make careless purchases I later wish I had not.
23. I take the time to shop carefully for best buys.

Factor 7 — Confused by Overchoice Consumer
24. There are so many brands to choose from that often I feel confused.
25. Sometimes it's hard to choose where to shop.
26. The more I learn about products, the harder it seems to choose the best.
27. All the information I get on different products confuses me.

Factor 8 — Habitual, Brand-Loyal Consumer
28. I have favorite brands I buy over and over.
29. Once I find a product or brand I like, I buy it regularly.
30. I go to the same retail outlets each time I shop.
31. I change brands I buy often.

Data Analysis and Findings

Best-Worst Scaling of Preferences for Attributes of a LS site

Testing the hypotheses of the study regarding the relative attractiveness of the attributes of a LS site relied on Best-Worst Scaling (BWS) and its extension within the Multinomial Logit (MNL) modeling framework (Aziaki & Fogarty, 2019; Louviere et al., 2015; Marley & Louviere, 2005). Analysis of the responses to the best-worst scaling questions used both the "counting approach" and the modeling approach (MNL) (Aziaki & Fogarty, 2019) discussed above.

Counting Approach
Using the notation in Aziaki and Fogarth (2019), the counting approach calculates Best-Worst (BW) scores for each respondent n and for each level i of an attribute across all questions for a respondent (16 in the current study) as follows:

B_{in} : Number of times respondent n selected level i as the best
W_{in} : Number of times respondent n selected level i as the worst
$BW_{in} = B_{in} - W_{in}$

Since the number of times levels of attributes appear in a questionnaire may vary across attributes BW_{in} scores are standardized taking into account the frequency f_i with which each level i appears across the whole questionnaire for a given subject:

$$std. BW_{in} = \frac{BW_{in}}{f_i}$$

These scores reflect respondents' preferences for different levels of attributes. In the current study f_i is eight for the attribute with two levels (prices similar or lower than elsewhere) and four for the remaining attributes with four levels each.

Modeling Approach
The modeling approach relies on the discrete choice models (Multinomial Logit (MNL) and its variations) since best worst scaling scores are related to the random utility model given certain assumptions (Louviere et al., 2015; Marley & Louviere, 2008). A key assumption is that the "utility", "attractiveness" or "importance" of the level chosen as the worst is the negative of the level chosen as the best. As discussed in the previous chapter, researchers have suggested the paired, marginal and marginal sequential models depending on the assumptions regarding how the respondents of a BW scaling study responds to questions and chooses the best and worst levels for a given profile in a BWS Case 2 study (Aziaki & Fogarth, 2019; Louviere et al.,2015). Aziaki and Fogarth (2019, Table 1, p. 4) present nine variations of these three types of models based on published empirical works where the variations depend on whether the attribute variables are represented in the related MNL models and whether the levels of attributes are effect or dummy coded. Three models, one for paired, marginal and marginal models, were selected such that attribute levels were not represented in the MNL logit model and the same base level ("prices are the same as elsewhere") was used for all three types of models. The selected models allow for a direct comparison of the estimated model parameters across all levels

of all attributes. For example, logit regression coefficients reflecting the relative attractiveness of each level of any attribute can be compared to levels of the same attribute as well as the levels of other attributes directly. Hypotheses can be tested to compare of the related logit coefficients that reflect the "utility" or the "importance" of two attribute levels.

The three models used in this study are models two, six, and nine in Table 1 of Aizaki and Fogarth (2019, p.4) that provide functions to construct discrete choice coding for the variants of the MNL logit model and compute BWS Case 2 count-based scores for the selected models given the best-worst responses of the respondents. Count-based BWS2 scores were computed using the R package Support.BWS2 in this study.

The relative attractiveness of the levels of the attributes of LS sites are the focus of this study. The best worst scores associated with the levels of the attributes are the variables of the analyses presented below. Since the variables are mentioned throughout the discussion in this chapter the variable names and the associated levels of attributes are summarized in Table 4 on the next page.

Counting Approach: Descriptive Statistics

Table 5 presents the best B_{in}, worst W_{in} , best minus worst BW_{in} and standardized best minus worst scores $std.BW_{in}$ summed across the sample. Table 6 presents the descriptive statistics for standardized best word scores $std.BW_{in}$. The rows of Table 6 are ranked according to the mean $std.BW_{in}$ from the highest to the lowest.

In Table 5 larger positive scores for BW_{in} and $std.BW_{in}$ indicate that the frequency with which the respondents selected the related attribute as the best attribute is relatively high. Similarly, larger negative scores for BW_{in} and $std.BW_{in}$ indicate that the frequency with which the respondents selected the related attribute to be the worst attribute is relatively high. Differences in these summed (aggregate) scores across the levels of the attributes suggest the relative importance (attractiveness, utility) of the attribute levels to the respondents. A quick review of the summed $std.BW_{in}$ scores suggest that the generation Z sample of consumers perceive lower prices (0.436), host characteristics (knowledgeable and entertaining: 0.288), (knowledgeable, entertaining and authentic: 0.350) and new and unique products (0.098) at a LS site as potentially engaging. The respondents perceive a LS site with prices similar to other outlets (-0.255), not offering any interaction (-0.294), marketing known brands and designs that can be found elsewhere in other outlets (-0.210) and marketing new brands but not uniquely designed products (-0.245) not engaging.

Table 4. Variable Names for Levels of Attributes

Attribute	Variable Names and Associated Levels of Attribute			
	1	2	3	4
Host	Knwledgbl	Entertng	KnwlEntert	KnwlEntertAuth
	Knowledgeable	Entertaining	Knowledgeable, Entertaining	Knowledgeable, Entertaining, Authentic
Price	Lower Price	Similar Price to other outlet		
	Lower than other retail outlets	Similar to other retail outlets		
Interactivity	NoInteract	ConsText	ConsStafText	CSTextHostResp
	No Interaction	Consumers can text	Consumers and Staff text each other	Consumers can text, host can respond live
Marketed Products	BeautyCosm	ClothFashn	FoodCook	ConsElectr
	Beauty Products, Cosmetics	Clothing, Fashion	Food, Cooking Related	Consumer Electronics
Brand, Uniqueness of Design	KnownMarktdElswr	KnownUniq	NewSimElswr	NewUniq
	Known Brands, Marketed Elsewhere	Known Brands, Unique Design	New Brands, Similar design marketed elsewhere	New Brands, Unique Designs

Table 5. Summed Best Worst Scores

Attribute Level	Best	Worst	Best-Worst	Standardized Best-Worst [a]
Lower	988	105	883	0.460
KnwlEntertAuth	397	44	353	0.368
KnwlEntert	346	52	294	0.306
NewUniq	229	129	100	0.104
ClothFashn	188	131	57	0.059
KnownUniq	186	130	56	0.058
Entertng	188	136	52	0.054
Knwledgbl	158	110	48	0.050
CSTextHostResp	238	208	30	0.031
ConsStafText	185	219	-34	-0.035
ConsText	125	224	-99	-0.103
ConsElectr	92	197	-105	-0.109
BeautyCosm	135	247	-112	-0.117
KnownMarktdElswr	86	302	-216	-0.225
FoodCook	50	281	-231	-0.241
NewSimElswr	53	309	-256	-0.267
NoInteract	48	342	-294	-0.306
Similar	148	674	-526	-0.274

a) Based on aggregate best-worst scores.

Table 6 complements the above data providing additional descriptive statistics regarding the standardized best worst scores $std.BW_{in}$ for all levels of attributes. Nine of the top ranked attribute levels have positive and nine of the bottom ranked attributes have negative **means** for $std.BW_{in}$. As mentioned above, generation Z consumers perceive lower prices (0.436), hosts who are (knowledgeable, entertaining and authentic 0.350) and (knowledgeable and entertaining 0.288), uniqueness of brands (0.098) and designs (0.055) marketed as potentially engaging. It is important to note that lower price is a very important attribute (0.436).

No price advantage (similar prices elsewhere) and no interaction at a LS site decrease potential engagement the most among the levels of attributes considered (-0.225 and -0.294, respectively).

Attributes that seem to reduce desire for engagement are marketing known brands and new brands that are marketed elsewhere (-0.210 and -0.245, respectively). Marketing beauty products and cosmetics and food cooking do not seem to motivate engagement with a LS site (-0.115 and -0.225, respectively). As discussed below this surprising finding is due to gender differences. While female generation Z consumers perceived availability of beauty products and cosmetics as a relatively attractive attribute of a LS site male respondents do not.

Table 6. Descriptive Statistics for Standardized BWS Scores

Attribute Level	Rank Based on Mean [a]	Mean	Standard Deviation	Median	Skewness	Kurtosis
Lower	1	0.436	0.383	0.438	-0.304	-0.090
KnwlEntertAuth	2	0.350	0.336	0.250	-0.106	0.655
KnwlEntert	3	0.288	0.361	0.250	0.121	0.349
NewUniq	4	0.098	0.396	0.000	-0.022	0.312
KnownUniq	5	0.055	0.347	0.000	-0.116	0.122
ClothFashn	6	0.053	0.399	0.000	0.318	0.304
Knwledgbl	7	0.052	0.365	0.000	0.522	0.927
Entertng	8	0.049	0.391	0.000	0.327	0.756
CSTextHostResp	9	0.031	0.461	0.000	-0.234	-0.450
ConsStafText	10	-0.037	0.434	0.000	-0.166	0.011
ConsText	11	-0.096	0.372	0.000	0.253	0.623
ConsElectr	12	-0.110	0.333	0.000	-0.134	1.070
BeautyCosm	13	-0.115	0.456	0.000	0.113	-0.047
KnownMarktdElswr	14	-0.210	0.337	-0.250	-0.030	0.102
FoodCook	15	-0.225	0.358	-0.250	-0.182	0.533
NewSimElswr	16	-0.245	0.334	-0.250	0.003	0.402
Similar	17	-0.255	0.368	-0.250	0.213	0.262
NoInteract	18	-0.294	0.380	-0.250	-0.163	-0.182

a) Ranking is from the highest to the lowest.

Properties of Best-Minus-Worst Scores and Frequencies

Louviere et al. (2015, p.116) indicate that various uses of best worst scores are "simple first approximations" of the underlying true utilities (utilities, importance, preferences). They also note (p.116) that the set of best-minus-worst frequencies are a sufficient statistic for the maxdiff model (Marley & Louviere, 2005; Marley & Pihlens, 2021) and the set of best-minus-worst scores "…have been found to exhibit a high linear correlation with the true values of the random utility scale" (Louviere, 2015, p. 117). Finn and Louviere (1992) and Louviere et al. (2004) used best-minus-worst frequencies as approximations of a utility scale. Cheung et al. (2019) preferred standardized best-minus-worst frequencies rather than best-minus-worst scores. Marley and Louviere (2005) used the square root of the ratio of the best to worst frequencies.

Louviere et al. (2015, p. 117) indicate also that modeling the random nature of utility such as the paired model in this study can provide "more sophisticated estimates" of the related parameters reflecting the utilities of objects and levels of attributes. These estimates provide an interval scale of the levels of attributes in the Case 2 model considered here. The origin and the scale of this measure is arbitrary but differences of the coefficients are meaningful.

Although the differences across the means of the standardized best-minus-worst scores for different attribute levels seem to be in the direction expressed in the chapter on the hypotheses of

the study, it is important to regard them as approximations related to random utility coefficients. For this reason, conditional logistic regression is applied to the $std.BW_{in}$ data. Hypotheses H1 through H5 are tested using the estimated conditional logistic regression coefficients.

Modeling Approach: Conditional Logistic Regression

Data sets for three different multinomial regression models, the paired model, the marginal model, and the marginal sequential model, were constructed for Models 2, 6, and 9 of the classification presented by Aizaki and Fogarty (2019a, p.4) using R package Support.BWS2 (Aizaki & Fogarty, 2019b). The sample size of the study is $n = 240$ (129 females and 111 males) and each respondent evaluates $q = 16$ different questions (LS profiles) constructed according to an orthogonal main effects experimental design.

The paired model assumes that when subjects indicate a best and a worst attribute level in a profile, they consider $Kx(K-1) = 20$ all possible pairs of $K = 5$ profile attributes. Hence the data matrix for *each* subject is expanded into a matrix with $q \, x \, K \, x \, (K-1) = 320$ rows. Thus, the data matrix for the paired model for 240 subjects has $n \, x \, q \, x \, K \, x \, (K-1) = $ 240 x 16 x 20 =76,800 rows. On the other hand, the marginal model assumes that subjects consider an attribute level the best among $K = 5$ levels and the worst among $K = 5$ levels. So, the data matrix is expanded to a matrix with $n \, x \, q \, x \, (K+K) = $ 240 x 16 x (5+5) = 38,400 rows. Finally, the marginal sequential model assumes that when subjects choose a best and a worst level in a given profile, first they consider K choices for the best level, and then choose the worst level among the remaining $(K-1)$ levels. So, the data matrix is expanded to a matrix with $n \, x \, q \, x \, (K+K-1) = $ 240 x 16 x (5+4) = 34,560 rows. In all three models the number of rows of the data matrix increases because of subjects reporting both the worst choice and the best choice and having multiple observations from the same subject (16 in the current case) (Louviere et al., 2015). This is an advantage of best worst scaling in comparison of discrete choice modeling where the subjects report only their best choice. Also, the assumptions about how the subjects choose the best and the worst alternatives for a given profile increases the number of rows differently depending on if a paired, marginal or marginal sequential model is assumed.

After transforming the observed best worst scores into three datasets corresponding to the three types of MNL models (Aizaki & Fogarth, 2019), R package Mlogit (Croissant, 2020) was used to estimate the parameters of the related logit regressions. Comparison of the three models as presented in Table 7 involved AIC (Akaike's Information Criterion) (Akaike, 1974; 1981) and BIC (Bayesian or Schwarz Information Criterion).

$$AIC = 2k - 2\ln(\hat{L})$$
$$BIC = \ln(n)\,k - 2\ln(\hat{L})$$

where k is number of parameters, n is number of observations, and $\hat{L}$ is estimated likelihood for a given MNL model. Both measures assess the likelihood and complexity of a model in terms of number of estimated parameters and support models with lower values. Table 7 shows the information criteria for the three models. Model 2 was preferred over the remaining two models since the AIC and BIC values are lower for Model 2 (20,258.55 and 20,364.86, respectively).

Table 7. Comparison of Logistic Regression Models

	Log Likelihood	df	Sample Size	AIC	BIC
Model 2	-10112.28	17	3840	20,258.55	20,364.86
Model 6	-10664.30	17	3840	21,362.61	21,468.91
Model9	-10468.82	13	3840	20,963.64	21,044.93

The following Table 8 presents the logistic regression results

Table 8. Model 2 Logistic Regression Results

Rank	Attribute	β	exp(β)	se(β)	z	p-value
1	Lower Prices	2.088	8.072	0.057	36.66	0.000 ***
2	KnwlEntertAuth	1.784	5.952	0.068	26.07	0.000 ***
3	KnwlEntert	1.626	5.086	0.068	23.90	0.000 ***
4	NewUniq	1.187	3.276	0.067	17.77	0.000 ***
5	KnownUniq	1.067	2.907	0.066	16.08	0.000 ***
6	ClothFashn	1.059	2.883	0.067	15.86	0.000 ***
7	CSTextHostResp	0.960	2.611	0.065	14.71	0.000 ***
8	Entertng	0.883	2.418	0.066	13.48	0.000 ***
9	Knwledgbl	0.868	2.383	0.066	13.16	0.000 ***
10	ConsStafText	0.757	2.131	0.066	11.55	0.000 ***
11	CosunsText	0.612	1.845	0.066	9.22	0.000 ***
12	ConsElectr	0.586	1.797	0.066	8.95	0.000 ***
13	BeautyCosm	0.567	1.763	0.066	8.62	0.000 ***
14	KnownMarktdElswr	0.215	1.240	0.065	3.31	0.001 ***
15	FoodCook	0.155	1.168	0.065	2.37	0.018
16	NewSimElswr	0.063	1.065	0.065	0.97	0.333
17	NoInteract	-0.047	0.955	0.065	-0.72	0.474
18	Similar prices elsewher[a]	0.000				

β: Logistic regression coefficient, $se(\beta)$: standard error of β, $z = \beta/se(\beta)$

a) "Similar prices elsewhere" was the base level for the logistic regression model.

Table 9 below presents the estimated conditional logistic regression coefficients along with the means of the standardized best worst scores for levels of attributes so that the results of the counting approach and the modeling approach can be easily compared. As discussed before, conditional logit estimation of regression coefficients associated with the best-worst scores in a random utility model enables the estimation of relative importance on an interval scale. The means of the standardized best worst scores are approximations of the true utilities (preferences).

As presented in Table 9, the rankings of the levels of attribute from the highest to the lowest agree with the rankings of the logistic regression coefficients except for three levels of attributes (Knwledgbl, Entertng, CSTesxtHostResp) that are clustered together on the importance scale. The correlation of the mean standardized best worst scores and the logistic regression coefficients is 0.995.

Table 9. Mean STBWS Scores and Logistic Regression Coefficients for Attribute Levelsa

Rank Order	Attribute Level	Mean STBWS[b]	Rank Order	Attribute Level	Logistic Regression Coefficient
1	Lower	0.436	1	Lower	2.088
2	KnwlEntertAuth	0.350	2	KnwlEntertAuth	1.784
3	KnwlEntert	0.288	3	KnwlEntert	1.626
4	NewUniq	0.098	4	NewUniq	1.187
5	KnownUniq	0.055	5	KnownUniq	1.067
6	ClothFashn	0.053	6	ClothFashn	1.059
7	Knwledgbl	0.052	7	CSTextHostResp	0.960
8	Entertng	0.049	8	Entertng	0.883
9	CSTextHostResp	0.031	9	Knwledgbl	0.868
10	ConsStafText	-0.037	10	ConsStafText	0.757
11	ConsText	-0.096	11	ConsText	0.612
12	ConsElectr	-0.110	12	ConsElectr	0.586
13	BeautyCosm	-0.115	13	BeautyCosm	0.567
14	KnownMarktdElswr	-0.210	14	KnownMarktdElswr	0.215
15	FoodCook	-0.225	15	FoodCook	0.155
16	NewSimElswr	-0.245	16	NewSimElswr	0.063
17	Similar	-0.255	17	Similar	0.000
18	NoInteract	-0.294	18	NoInteract	-0.047

a) Correlation of Mean STBWS and logistic regression coefficients is 0.995.
b) Mean STBWS: Mean of the Standardized Best Worst Scores.

Hypothesis Testing

The hypotheses of the study were tested using the logistic regression coefficients for Model 2 presented in Table 8. The coefficients represent the log odds of preferring the levels of a LS site over the base level "prices are similar to prices elsewhere". Table 8 displays the coefficients, their exponential expressions as probability of choosing attribute levels over "prices are similar to prices elsewhere", standard errors of the coefficients, and the associated z value for testing the hypothesis that each coefficient is equal to zero and the p-value related to each z-test. Z-tests and the associated p-values suggest the generation Z consumers perceive only "no interaction" at a LS site and marketing "new brands that are similar to brands elsewhere" as not more important than the base level of "prices are similar to prices elsewhere". 14 of the 17 attribute levels are greater than the base level with very small p-values close to 0.000.

At presented in Table 8, hypothesis H1 is confirmed (z=36.66, p-value = 0.000). The regression coefficient is positive indicating the consumers perceive the "lower prices at a LS site" more engaging than the sites with no price advantages.

Table 10. Comparison of Logistic Regression Coefficients

Hypothesis Label	Hypothesis Tested[b]	χ^2	df	p-value	Conclusion
H1	$\beta_1 = 0$	1,343.7	1	0.000	$\beta_1 > 0.0$
H2A	$\beta_2 = \beta_9$	130.7	1	0.000	$\beta_2 > \beta_9$
H2B	$\beta_2 = \beta_8$	128.0	1	0.000	$\beta_2 > \beta_8$
H2C	$\beta_2 = \beta_3$	3.8	1	0.051	$\beta_2 > \beta_3$
H3A	$\beta_7 = \beta_{18}$	161.1	1	0.000	$\beta_7 > \beta_{18}$
H3B	$\beta_7 = \beta_{11}$	19.7	1	0.000	$\beta_7 > \beta_{11}$
H3C	$\beta_7 = \beta_{10}$	6.8	1	0.009	$\beta_7 > \beta_{10}$
H4A	$\beta_4 = \beta_{14}$	150.4	1	0.000	$\beta_4 > \beta_{14}$
H4B	$\beta_4 = \beta_{16}$	197.9	1	0.000	$\beta_{17} > \beta_{16}$
H4C	$(\beta_4 + \beta_5)/2 = (\beta_{14} + \beta_{16})/2$	307.2	1	0.000	$(\beta_4 + \beta_5)/2 > (\beta_{14} + \beta_{16})/2$
H5A	$\beta_6 = \beta_{12}$	35.7	1	0.000	$\beta_6 > \beta_{12}$
H5B	$\beta_{12} = \beta_{13}$	0.06	1	0.810	$\beta_{12} = \beta_{13}$

a) Wald's χ^2 test.
b) β_j : j indicates attribute level number in Table 9.

In the modeling approach, the remaining hypotheses require comparing one logit coefficient related to a level of a LS attribute to another level of the same attribute or a level of another attribute. For this purpose, one can put restrictions on the model likelihood (for example the equality model parameters) and use tests like the likelihood ratio test, Lagrange test and Wald test (Long, 1997, pp. 87-98). In this study Wald's χ^2 test was used simply because it was available as a function in the R package Mlogit (Croissant, 2020) that was used also for the estimation of the logit coefficients.

Table 10 above presents the results of hypothesis tests for hypotheses H2A through H5B. All hypotheses regarding the equality of pairs of logit coefficients are rejected with p-values of 0.009 or less except for H2C with a p-value of 0.051. Hypothesized logit coefficients are higher for the expected levels of attributes against the remaining levels of the same attribute suggesting generation Z preferences for them in engagement with a LS site. As far as host characteristics at

a LS site are concerned (hypotheses H2A, H2B, and H2C), a (knowledgeable, entertaining and authentic) host with all three qualifications is preferred to a host who may be only knowledgeable or entertaining or both knowledgeable and entertaining. It seems that a host needs to have all three qualifications to sustain engagement with generation Z consumers.

Hypotheses H3A, H3B, and H3C deal with the type and degree of interactivity at a LS site. No interaction, consumer posting of messages at a LS site, staff members at a LS site responding to message posted by viewers, and the host personally joining in interaction live along with the staff and consumers exchanging messages reflect increasing variety and levels of interactivity. Live interaction with the host along with the messages exchanged between the consumers and the staff members is the level of interactivity preferred to others as suggested by the results of Ward's tests with p-values less than 0.01 in Table 10. As expected, interactivity with simultaneously used various forms of interaction including host participation is important for generation Z.

As discussed in the literature review chapter, generation Z consumers are interested in new brands and unique designs. Hypotheses H4A, H4B, and H4C are about two crossed experimental factors: (1) Known versus new brands, and (2) Unique designs versus designs available in outlets other than a LS site that the consumer may consider for engagement. Crossing these two factors creates four possibilities. They were included in the design of the BWS2 questionnaire as four levels of "brand and uniqueness" attribute. Table 10 shows that all three hypotheses were confirmed with p-values 0.01 or less. Generation Z consumers prefer LS sites offering new brands with unique designs to LS sites with known and familiar designs available elsewhere (H4A), and LS sites with new brands but designs available elsewhere (H4B). Uniqueness of the designs offered at a LS site seems to be a major attractive attribute for generation Z. H4C test further confirms the effect of unique designs for both new and known brands that are unique versus both new and known brands with designs available at other retail outlets.

Hypotheses H5A and H5B are about which product categories the generation Z consumers will perceive to be more relevant for engagement with a LS site. Generation Z consumers are expected to consider clothing and fashion items (H5A) and beauty products and cosmetics (H5B) to be more engaging than consumer electronics based on sales data as discussed in the literature review chapter. Ward's test confirms H5A that clothing and fashion products are more engaging than electronics ($\chi^2 = 35.7, df = 1, p = 0.000$). But the null hypothesis H5B that beauty products and cosmetics are more engaging than consumer electronics cannot be rejected ($\chi^2 = 35.7, df = 1, p = 0.000$). This result may be due to the makeup of the sample having 129 females and 111 males. Females may have chosen beauty products and cosmetics as their "best" choices while males may have chosen "electronics". This may have resulted in the observed finding.

Gender Differences in the Mean Standardized Best Worst Scores
H6A through H7A presented in the previous chapter involve some hypotheses regarding gender differences. Although it is possible to model the BWS2 responses using the logit framework for each gender and estimate the related logit regression coefficients for two models, it is controversial to compare coefficients on two different logit models (Williams, 2009). For this reason, the mean and standard deviation values of the standardized BWS2 scores were calculated for the levels of attributes for females and males, and the related means were compared using t-tests. Table 11 presents the mean and standard deviation values for the levels of LS attributes for females and males.

Table 11. Rank Ordered Means of Standardized BWS for Females and Males

	Females			Males	
Rank Order[a]	Attribute Level	Mean STBWS[b]	Rank Order	Attribute Level	Mean STBWS
1	Lower Price	0.450	1	KnwlEntertAuth	0.426
2	KnwlEntertAuth	0.285	2	Lower Price	0.421
3	KnwlEntert	0.271	3	KnwlEntert	0.306
4	ClothFashn	0.157	4	CSTextHostResp	0.115
5	BeautyCosm	0.108	5	Entertng	0.114
6	NewUniq	0.102	6	NewUniq	0.095
7	KnownUniq	0.061	7	KnownUniq	0.047
8	Knwledgbl	0.057	8	Knwledgbl	0.045
9	Entertng	-0.006	9	ConsStafText	0.045
10	CSTextHostResp	-0.042	10	ConsElectr	-0.034
11	ConsStafText	-0.108	11	ConsText	-0.055
12	ConsText	-0.132	12	ClothFashn	-0.069
13	ConsElectr	-0.175	13	KnownMarktdElswr	-0.204
14	FoodCook	-0.177	14	Similar Price	-0.244
15	KnownMarktdElswr	-0.215	15	NewSimElswr	-0.247
16	NewSimElswr	-0.244	16	FoodCook	-0.280
17	Similar Price	-0.265	17	NoInteract	-0.284
18	NoInteract	-0.302	18	BeautyCosm	-0.374

a) Rank Order: Ranked from the highest mean to the lowest mean.
b) STBWS: Standardized Best Worst Scores

Table 12 gives the results of t-tests that used Welch's (1947) correction for the calculation of degrees of freedom. The correction is used because the variances of the two groups are not assumed equal.

Table 12 shows that H6A, H6B, H6C and H7A involve gender differences. T-tests suggest that hypotheses of equal means across females and males are rejected at p-values close to zero. The alternative hypothesis that the expected mean of a given gender is greater than the mean of the other gender is accepted. Perceived importance of beauty products and cosmetics (H6A) and clothing and fashion products (H6B) is higher for females then males for engagement with a LS site. Perceived importance of beauty products and cosmetics for females is greater than the perceived importance of clothing and fashion product for males for engagement with a LS site (H6C). Males find LS sites offering electronics more engaging than females (H7A).

Table 12. Hypothesis Testing Regarding Gender Differences

Hypothesis Label	Means Involved[b]		Mean (Female)	Mean (Male)	t-value	df[a]	p-value
	Female	Male					
H6A	Beauty Cosmetics	Beauty Cosmetics	0.1076	-0.3739	9.6097	234.44	0.0000
H6B	Clothing Fashion	Clothing Fashion	0.1570	-0.0687	4.5716	237.07	0.0000
H6C	Beauty Cosmetic	Clothing Fashion	0.1076	-0.0687	3.5993	236.54	0.0004
H6D	Beauty Cosmetics, Consumer Electronics,		0.1076 -0.1754		6.1726	251.22	0.0000
H6E	Clothing Fashion, Consumer Electronics		0.1570 -0.1754		7.1845	250.09	0.0000
H7A	Consumer Electronics	Consumer Electronics	-0.1754	-0.0338	3.3800	237.54	0.0008
H7B		Consumer Electronics, Beauty Cosmetics		-0.0338 -0.3739	7.3111	210.30	0.0000

a) Variances of the two subsamples (female, male) are not assumed equal. Welch's (1947) correction is used in the calculation of degrees of freedom.

Hypotheses H6E and H7B are within gender comparisons. Females perceive LS sites that offer clothing and fashion products more engaging than sites that offer electronics. Males consider LS sites that market electronics more engaging than sites that offer beauty products and cosmetics.

The following post hoc hypotheses H8A and H8B related to differences in gender preferences for the observed best levels of (1) prices and (2) brands and unique designs. The null hypothesis for each test is that the tested means for females and males are equal.

Table 13. Post- Hoc Hypothesis Testing Regarding Gender Differences

Hypothesis Label	Means Involved		Mean (Female)	Mean (Male)	t-value	df[a]	p-value
	FEM	MALE					
H8A	Lower Prices	Lower Prices	0.4496	0.4211	0.5745	234.77	0.5662
H8B	NewUniq	NewUniq	0.1017	0.0946	0.1386	226.95	0.8899

a) Variances of the two subsamples (female, male) are not assumed equal. Welch's (1947) correction is used in the calculation of degrees of freedom.

Hypothesis H8A that tests the equality of the attractiveness of lower prices for engagement with a LS site for female and males. This hypothesis is not rejected as presented in the first row of Table 13 (t= 0.5745, df=234.77, p-value = 0.566). Low prices seem to be equally attractive for both genders. Lower prices is a dominant LS attribute for engagement for all generation Z consumers. The absolute values of the related means of standardized BWS2 values for "lower prices" are 0.4496 and 0.4211 for females and males, respectively. The means for "prices similar to other competitors" are -0.2645 for females and -0.2444 for males. Price seems to be a very dominant attribute that may affect continued engagement with a LS site.

Finally, the results of H8B suggest that offering new brands and new designs at a LS site are equally important for females and males in their decision to engage with a LS site (t=0.1386, df=226.95, p-value = 0.8899).

Going back to Table 11 and reviewing the means for the standardized best worst scores for females and males it is interesting to note that similar attribute levels appear at the top and the bottom of the ranked means. These levels are lower prices, knowledgeable, entertaining and authentic host, and entertaining host. So, marketing products at lower prices and having hosts who are knowledgeable, entertaining and authentic are very more important for both genders. Moreover, it is meaningful to examine the differences in importance measures across levels within an attribute to understand the magnitude of increase in utility as a result of changing the levels of that attribute as it is done in conjoint analysis. The difference between the maximum and minimum preference (utility) measures for price and host characteristics at the top and the bottom of the rankings are relatively higher or equal to the remaining within attribute differences. This suggests that improvements in price and host characteristics are likely to improve the preferences of generation Z consumers as much as or more than the remaining attributes.

Factor Analysis of Shopping Styles Data

This section presents the results of the factor analysis of the shopping styles data collected from the sample of generation Z consumers. As mentioned in the literature review and the data collection chapters a revised version of the Sproles and Kendall's (1986) with 29 items was administered to the respondents.

Previous attempts to examine the replicability of Sproles and Kendall's (1986) factor analysis results across various countries discovered some differences from the factor structure reported by them. Although many of their factors were replicated, there were some additional and missing factors. Because considerable time elapsed since the publication of their result and new shopping alternatives emerged on the internet to affect consumers' shopping styles, an exploratory factor analysis (EFA) was performed in this study. Moreover, the objective of collection and analyzing the data regarding general shopping styles in this study is not to examine the psychometric properties of the instrument but to provide supplementary information regarding the general shopping preferences respondents and examine if they can assist as auxiliary information to interpret the findings suggested by BWS2 estimates. For these reasons some detail that is routinely reported in confirmatory factor analysis (CFA) contexts are not reported in this EFA and the discussion focuses on critical elements of the analysis and findings.

Table 14 below presents the questions associated with shopping style and the variable name associated with each statement. Respondents expressed their degree of agreement or disagreement with each statement on a Likert scale ranging from (1) strongly disagree to (7) strongly agree.

Table 14. Shopping Style Variable Names and Related Statements on the Questionnaire

Variable Name	Statement on Questionnaire
QUALIMP	Getting very good quality is very important to me.
PERFCH	When it comes to purchasing products, I try to get the very best or perfect choice.
BUYOVRQUAL	In general, I usually try to buy the best overall quality.
HISTNDBRND	My standards and expectations for products I buy are very high.
KNOWNBRND	The well-known national brands are best for me.
EXPNSVBRND	The more expensive brands are usually my choices.
BUYBSTSELLNG	I prefer buying the best-selling brands.
NEWSTYLE	I usually have one or more outfits of the very newest style.
UPTODATE	I keep my wardrobe up-to-date with the changing fashions.
FASHIONIMP	Fashionable, attractive styling is very important to me.
BUYVARIETY	To get variety, I shop different stores and choose different brands
SHPNOTPLSNT	Shopping is not a pleasant activity to me.
SHOPENJOY	Shopping is one of the enjoyable activities of my life.
SHPWSTIM	Shopping wastes my time.
ENJOYSHP	I enjoy shopping just for the fun of it.
BUYSALEPR	I buy as much as possible at sale prices.
LOPRICECH	The lower price products are usually my choice.
BSTVALUE	I look carefully to find the best value for the money.
PLANCARFL	I should plan my shopping more carefully than I do.
IMPULSV	I am impulsive when purchasing.
CARELSPUR	Often I make careless purchases I later wish I had not.
TAKETIME	I take the time to shop carefully for best buys.
CONFUSED	There are so many brands to choose from that often I feel confused.
HARDTOCH	Sometimes it's hard to choose where to shop.
LEARNHRDR	The more I learn about products, the harder it seems to choose the best.
INFOCONFUSE	All the information I get on different products confuses me.
FAVBRNDS	I have favorite brands I buy over and over.
BUYREGULR	Once I find a product or brand I like, I buy it regularly.
SAMETRLOUT	I go to the same retail outlets each time I shop.
CHNGBRND	I change brands I buy often.

Likert-scales ranging from (1) strongly disagree to (7) strongly agree

Table 15 shows the related descriptive statistics for the variables of the shopping style data. The correlation matrix for the shopping style variables is a large 29 by 29 matrices. It is not presented due to its size.

Table 15. Descriptive Statistics for Shopping Style Variables

Variable Number	Variable Name	Mean	Standard Deviation	Skewness	Kurtosis
1	QualImp	5.600	1.293	-1.128	1.293
2	PerfCh	5.608	1.337	-1.000	0.483
3	BuyOvrlQual	5.454	1.134	-0.761	0.822
4	HiStrndBrnd	4.850	1.304	-0.556	0.022
5	KnownBrnd	4.183	1.432	-0.058	-0.778
6	ExpnsvBrnd	3.321	1.574	0.311	-0.838
7	Confused	3.958	1.555	0.002	-0.982
8	BuyBstSellng	4.254	1.437	-0.255	-0.693
9	NewStyle	4.100	1.721	-0.164	-1.082
10	UpToDate	4.150	1.732	-0.255	-1.059
11	FashionImp	4.992	1.498	-0.641	-0.184
12	BuyVariety	4.821	1.401	-0.517	-0.539
13	ShpNotPlsnt	2.779	1.678	0.819	-0.354
14	ShpEnjoy	4.717	1.717	-0.393	-0.862
15	ShpWstTm	2.871	1.683	0.685	-0.477
16	EnjoyShp	4.421	1.851	-0.297	-1.060
17	BuySalePr	4.533	1.659	-0.373	-0.821
18	LoPrCh	4.125	1.526	-0.020	-0.729
19	BestValue	5.388	1.205	-0.787	0.632
20	Impulsv	3.954	1.724	-0.295	-1.099
21	CarelsPur	3.925	1.637	-0.068	-1.101
22	TakeTime	5.083	1.360	-0.557	-0.200
23	HardToChs	4.471	1.610	-0.307	-0.958
24	LearnHrdr	4.425	1.591	-0.140	-0.954
25	InfoConfuse	3.575	1.400	0.234	-0.926
26	FavBrnds	5.400	1.250	-0.809	0.572
27	BuyRegulr	5.283	1.204	-0.525	0.023
28	SameRtlOutlt	4.421	1.561	-0.373	-0.663
29	ChngBrnd	3.629	1.423	0.286	-0.588

Likert-scales ranging from (1) strongly disagree to (7) strongly agree

KMO sampling adequacy statistics were calculated for the individual variables and the whole set of variables to assess if the shopping style data set is suited for factor analysis for each variable and for the whole set of variables (Kaiser 1970; Kaiser & Rice 1974). KMO statistic represents the variance that may be associated with common variance and it ranges between 0.0 and 1.0 with higher values indicating higher common variance and thus data more suited for factor analysis. Values less than 0.5 are unacceptable. Values in the 0.60, 0.70, 0.80 and 0.90's were labeled mediocre, middling, meritorious and marvelous, respectively (Kaiser & Rice, 1974). Variables

with KMO less than 0.5 become candidates for exclusion from factor analysis. Following this guidance, a variable representing responses to Likert scale "I should plan my shopping more carefully than I do" was eliminated from factor analysis since its KMO statistic was 0.47. 13 of the KMO statistics for the shopping style data were in the 0.80's, 10 values in the 0.70's and the remaining six values were in the 60's for 29 variables. Overall KMO value for all 29 variables is 0.79 suggesting that shopping style data is suited for factor analysis.

Table 16 summarizes model fit statistics for exploratory factor analysis results for the shopping style data varying number of factors 3 to 10. The results suggest that 10 factor model fits the data better than the models with lower number of factors (Chi-square=0.947, df=161, p-value=0.127). RMSEA (root mean square error of approximation) is an absolute fit index that measures how far a hypothesized model is far from a perfect model. Hu and Bentler (1999) suggested an RMSEA value lower than 0.06. Bayesian Information Criterion (BIC) is a likelihood-based model comparison criterion with a penalty term to assess model fit. The model with a lower value indicates better fit. In this study, the lowest BIC value (-700.77) is for EFA with 10 factors. Tucker-Lewis Index (TLI) is an index of relative decrease in misfit per degree of freedom (Tucker & Lewis, 1973). Hu and Bentler (1999) recommend TLI values greater than 0.95. For the model with 10 factors TLI is 0.974.

Table 16. Model Fit Statistics for EFA of Shopping Style Data

Number of Factors	Chi-Square	df	p-value	BIC	TLI	RMSEA	L[a]	U[a]
3	1111.377	322	0.000	-877.697	0.658	0.085	0.079	0.092
4	777.501	296	0.000	-930.232	0.739	0.075	0.068	0.082
5	482.214	271	0.000	-952.027	0.810	0.063	0.056	0.072
6	256.404	247	0.000	-970.963	0.892	0.048	0.038	0.057
7	199.280	224	0.000	-901.926	0.910	0.043	0.033	0.054
8	152.438	202	0.001	-838.440	0.935	0.037	0.024	0.048
9	119.084	181	0.037	-775.655	0.961	0.028	0.008	0.042
10	97.446	161	0.127	-700.707	0.974	0.023	0.000	0.039

a) L and U indicate the lower and upper limits of the confidence interval for RMSEA with a p-value = 0.90.

An examination of the loadings and the explained variance for each factor for the ten-factor model revealed, however, that only one of the 29 variables had a loading of 0.32 for the 10th factor with remaining loadings being less that 0.20. The 10th factor accounted for only 1.2 percent of the explained variance. Moreover, Horn's Parallel Analysis (1965) with the adjustment by Goldfelt (1995) comparing the eigenvalues of the factor model with those obtained from random data suggested nine factors underlie the observed data as presented in Figure 3 below (Revelle, 2022). Observed eigenvalues of the factor model just exceed the 95th percentile of the eigenvalues from simulated random data up to and including nine factors. Parallel analysis is reported to be one of the best empirical methods to decide on the number of factors in EFA as reviewed by Dinno (2009). Given these considerations and seeking model parsimony, a nine-factor model was preferred to a ten-factor model.
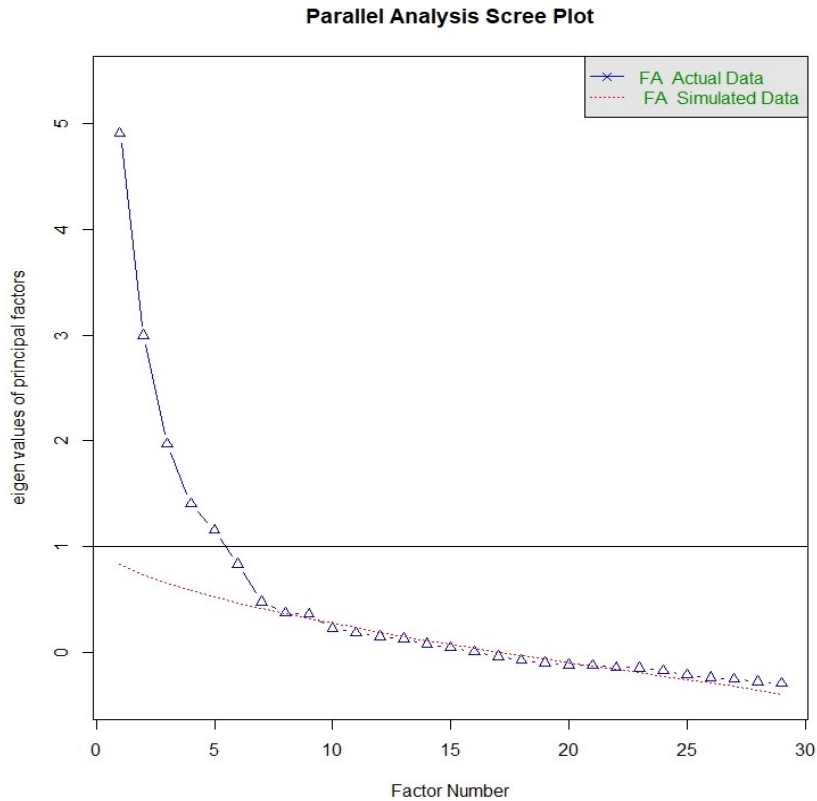
Parallel Analysis Scree Plot

Figure 3. Scree Plot for Horn's (1965) Parallel Analysis

Table 17 shows the estimated loadings for nine factors. Loadings less that 0.25 are suppressed for ease of interpretation. Factor loadings matrix was rotated using varimax algorithm and factor scores were computed based on Bartlett's method (Revelle, 2022). Nine factors explain 53.2 percent of total variance.

The factor structure presented in Table 17 somewhat overlaps with the factor structure that Sproles and Kendall (1986) presented more than 35 years ago. This study included only four items per factor that Sproles and Kendall (1986) included in their study. Despite this limitation, there are five factors where certain variables of their study load on the same factors as highlighted in grey in Table 17. Those factors are labeled using labels similar to those Sproles and Kendall (1986) originally suggested although the factor structure in Table 17 was not extracted using confirmatory factor analysis.

First factor represents a quality conscious consumer for whom quality is important (loading=0.705), who wants to buy the perfect choice or best quality (0.661). These consumers' standards for the products they buy are very high (0.834). They indicate that they take time to shop carefully (0.600) for best buys where "best buy" may actually mean "best quality" rather than "best price". The look for "best value" (0.478). The loading for the last item regarding "shopping carefully for best buys" was not high in Sproles and Kendall's (1986) study.

Second factor may be labeled recreational and hedonic consumer as in Sproles and Kendall (1986). As the highlighted loadings for this factor suggest these consumers disagree that shopping is not a pleasant activity (-0.784) and it wastes time (-0.766). On the contrary, they enjoy shopping (0.716). They also indicate fashion is important to them (0.406) and they like to

keep their wardrope up to date with the changing fashions (0.330). The fact that all these items load on the same factor may suggest that shopping that the consumer enjoys may be somewhat related to search for new fashion items.

The third factor is fashion consciousness. These consumers would like to have one or two items of the very recent fashions (0.751), they would like to keep their wardrope up to date with changing fashion items (0.779). They indicate that fashion is very important to them (0.509).

The fourth factor represents consumers who are confused by over choice (0.687). Information about different products confuses them (0.507). The more they learn about new products the harder it gets to make a product choice (0.826).

The fifth factor describes consumers who are loyal to brands and outlets. They have favorite brands (0.584). Once they find a brand they like, they tend to buy it regularly (0.514). They go to the same retail outlets when they shop (0.542). They are not interested in variety in terms of different shops or different brands (-0.359). They do not change brands often (-0.478).

The sixth factor relates to impulsive (0.549) consumers who think that they often make careless purchases (0.782).

The seventh factor represents consumers who are not price conscious. Lower priced products are not their choice (-0.509). They are not necessarily looking for the "best value" (-0.364). The consumers indicate that the more expensive products are their choices (0.653).

The eighth factor describes consume who buy known (0.919) and best-selling brands (0.373).

Finally, the ninth factor can be labeled as value seeker who buys at sale prices (0.582), changes brand often (0.398) possibly to take advantage of promotions. These consumers think that lower priced (0.372) and best value products are their choice (0.286).

Given the above factor structure and the estimated factor scores, mean factor scores were computed for each gender to test if there are any gender differences in shopping styles. Table 18 shows the results of the t-tests for gender differences for all nine factors.

Table 17. Factor Loadings and Explained Variance

	Quality Conscious	Recreational Hedonistic	Fashion Conscious	Confused by Overchoice	Brand Loyal	Impulsive	Not Price Conscious	Known Brand Buyer	Value Seeker
QualImp	0.705								
PerfCh	0.661								
BuyOvrlQual	0.834								
HiStrndBrnd	0.624								
TakeTime	0.600								0.261
ShpNotPlsnt		-0.784							
ShpEnjoy		0.716							
ShpWstTm		-0.766							
EnjoyShp		0.644					0.251		
NewStyle		0.263	0.751						
UpToDate		0.330	0.779						
FashionImp		0.406	0.509						
Confused				0.687					
LearnHrdr				0.507					
InfoConfuse				0.826					
FavBrnds					0.584				
BuyRegulr	0.277				0.514				
SameRtlOutlt					0.542				
Impulsv		0.282				0.549			
CarelsPur						0.782			

Table 17 Continued. Factor Loadings and Explained Variance

	Quality Conscious	Recreational Hedonistic	Fashion Conscious	Confused by Overchoice	Brand Loyal	Impulsive	Not Price Conscious	Known Brand Buyer	Value Seeker
ExpnsvBrnd							0.653		
LoPrCh							-0.509		0.372
KnownBrnd								0.919	
BuySalePr									0.582
BuyBstSellng	0.29							0.373	
BuyVariety		0.254			-0.359				
BestValue	0.478						-0.364		0.286
HardToChs				0.367					
ChngBrnd					-0.478				0.398

	Quality Conscious	Recreational Hedonistic	Fashion Conscious	Confused by Overchoice	Brand Loyal	Impulsive	Not Price Conscious	Known Brand Buyer	Value Seeker
SS Loadings	3.032	2.78	1.872	1.834	1.489	1.222	1.171	1.16	0.981
Proportion Var	0.105	0.096	0.065	0.063	0.051	0.042	0.04	0.04	0.034
Cumulative Var	0.105	0.2	0.265	0.328	0.38	0.422	0.462	0.502	0.536

Table 18. Gender Differences in Mean Factor Scores

Factor	Female	Male	Standard Error	t-value	df	p-value	L	U
Quality Conscious	-0.063	0.073	0.141	-0.964	229.076	0.336	-0.413	0.142
Recreational, Hedonistic	0.380	-0.442	0.135	6.113	214.198	0.000	0.557	1.088
Fashion Conscious	0.184	-0.214	0.149	2.673	219.956	0.008	0.104	0.691
Confused by Overchoice	0.256	-0.297	0.140	3.937	237.948	0.000	0.276	0.830
Brand Loyal	0.111	-0.129	0.158	1.513	218.895	0.132	-0.072	0.551
Impulsive	0.047	-0.055	0.158	0.649	218.974	0.517	-0.209	0.414
Not Price Conscious	-0.051	0.060	0.161	-0.687	234.764	0.493	-0.429	0.207
Known Brand Buyer	-0.199	0.231	0.129	-3.333	237.958	0.001	-0.685	-0.176
Value Seeker	0.118	-0.138	0.170	1.510	226.368	0.133	-0.078	0.591

L and U are lower and upper limites of confidence intervals with probability 0.90.

T-tests involving mean factor scores for gender differences suggest that female generation Z consumers, compared to males, are more hedonistic and recreational shoppers (t=6.113, df= 214.198, p-value=0.000), more fashion conscious (t=2.673, df=219.955, p-value=0.008), and more confused by overchoice (t-3.937, df=237.948, p-value=0.000). Male consumers, however, are more known-brand buyers (t= -3.333, df=237.958, p-value=0.001). The remaining mean factor scores are not statistically different between females and males.

One of the objectives of the second survey regarding shopping styles was to explore if general shopping styles for the two genders would shed light on the interpretation of the estimated relative importance of various levels of LS site attributes. The mean factor score for fashion consciousness for females (M= 0.184) is higher than the same factor scores for males (M = - 0.214) (t= 2.673, df= 219.955, p-value = 0.008). This gender difference in fashion consciousness in shopping is similar to the differences in the mean preference scores for LS sites offering clothing and fashion products (Females, M=0.157, Males, M= -0.069, t= 4.572, df = 237.07, p.value = 0.0000). So, stronger fashion consciousness of females as a general shopping style is reflected in the stronger preferences for LS sites offering clothing and fashion products.

The largest gender difference in the mean factor scores is for recreational and hedonistic shopping with higher mean for females (M=0.380) than males (M= -0.442) (t=6.113, p-value=0.000). This difference is expected based on prior research related to buying of hedonic products and enjoyment of shopping as an activity more so for females than males. However, the importance of an entertaining host (as an average of three levels of host characteristics (KnwlEntertAuth, M= 0.426, KnwlEntert, M=0.306, and Entertgn, M=0.114) is M= 0.282 for males. The same average for females with means (M=0.285, M=0.271, and 0.061, respectively)

is M=0.204. The t-test of the difference is with t= 2.020, df=223.82 and p-value= 0.045 suggesting higher importance of an entertaining host for the males, if multiple testing problem for post-hoc hypothesis testing is ignored. The discussion below addresses this issue. On the other hand, it is possible to consider the hedonic shopping as shopping for the products that the consumer enjoys and has emotional ties with. Thus, hedonic shopping may involve shopping for beauty products/cosmetics and clothing/fashion items as well as interactivity and entertainment at a LS site. In fact, hedonic shopping factor has a loading of 0.40 for FashionImp, "Fashionable, attractive styling is very important to me" and 0.330 for Uptodate, "I keep my wardrobe up-to-date with the changing fashions" both of which suggest that the underlying construct that is labeled "hedonic shopping" in this study is somewhat related to fashion. These findings suggest that further studies should attempt to differentiate enjoyment of interactivity and hedonic value of shopping for desired products better in the construction of the BWS questionnaire.

Another interesting finding is related to known brand buying. Mean factor scores for the male generation Z consumers of the study suggests that they engage in buying known (established) brands (M=0.231) more so than female buyers (M=-0.199) (t=-3.333, p-value=0.001). However, the average of the estimated relative preference measures for males for known brands with designs available elsewhere (M=0.047) or known brands with unique designs (M= -0.204) is not statistically different than the average of the corresponding means for females (M=0.061, M=-0.215, respectively). The difference in the averages of these importance measures is 0.022 with t= 0.678, df=237.98, p-value= 0.498. So, the observed difference in the factor scores for known brand buying is not reflected in the importance measures for the related LS attributes for the genders.

The above analysis included several post-hoc hypothesis tests conducted after observing the data. As the number of post-hoc hypotheses increases the potential for Type-I error for rejecting a null hypothesis when in fact it is true also increases. This is known as the multiple comparison or multiplicity problem (Bretz et al., 2011). For k independent tests each with a significance level α, the probability of not rejecting all null hypotheses when all hypotheses are true is $(1 - \alpha)^k$. For example, if $\alpha = 0.01$ and $k = 15$ tests are conducted, the probability of not making Type-I error is only 0.860 rather than 0.99. As a result, the probability of rejecting at least a true null hypothesis is $(1 - 0.860) = 0.14$ which is called "experimentwise error rate, $EER = 1 - (1 - \alpha)^k$, or familywise error rate (Bender & Lange, 2001). Procedures for simultaneous statistical inference have been suggested to control the familywise error rate (Bretz et al., 2011) or "false discovery rate" (FDR). False discoveries are "incorrect rejections of the null hypothesis". Benjamini-Hochberg (1995) method of adjustment for p-values associated with multiple hypotheses controls the false discovery rate (FDR).

As presented in Table 19, Benjamini and Hochberg's (1995) method was used to adjust the p-values for 14 post-hoc tests discussed above. Two post-hoc tests relate to gender differences presented in Table 13. Nine tests are about gender differences in mean factor scores presented in Table 18. Finally, three tests explore if the gender differences in mean factor scores are reflected in the related differences in the standardized best-worst scores.

Benjamini and Hochberg's (1995) method suggests that one of the calculated p-values, 0.045 is adjusted to 0.1050. This hypothesis is the one associated with the difference in the importance ratings for entertainment for males vs females. The adjustment results in not rejecting the equality of the importance of entertainment for females and males. Rejection of this hypothesis was a surprising finding that is reversed by this adjustment. The remaining ad-hoc hypothesis tests are not affected by the adjustment of the p-values.

Table 19. Benjamini-Hocberg (1995) Adjustment of P-values

p-value	Adjusted p-value
0.5562	0.6097
0.8899	0.8899
0.3360	0.5227
0.0001	0.0005
0.0080	0.0224
0.0001	0.0005
0.1320	0.2328
0.5170	0.6031
0.4930	0.6031
0.0010	0.0034
0.1330	0.2328
0.0001	0.0004
0.0450	0.1050
0.4980	0.6031

Conclusions

Major Findings

Livestream Shopping (LS), already an important retail alternative in China, is expected to grow rather rapidly in North America and increase its share of retail sales. At least initially, the target segments are likely to be Generation Z and Millennials since LS offers a combination of shopping and social media appealing to both young generations.

This study provided measures of the relative attractiveness (importance, utility) of some critical attributes (and their levels) of LS to generation Z. Based on the profile method of best-worst scaling also known as Case 2 Best Worst Scaling (Louviere et al., 2015), the estimated measures of relative attractiveness are on a common interval scale allowing comparisons across attributes and also between levels within attributes between. In this sense, relative attractiveness measures can be informative in the design and marketing of LS sites as conjoint analysis has been used for several decades. A clear advantage of best worst scaling, among other advantages discussed in this thesis, is that it allows for direct comparisons across attributes as well as across levels of attributes on the same scale. Only direct comparison of importance of levels of a given attribute was possible with conjoint analysis.

Random utility modeling of best worst judgments using logistic regression suggested that having lower prices than other outlets is the most important attribute among the five attributes included in the study. Next in importance is a knowledgeable, entertaining and authentic host. Somewhat lower in relative attractiveness is offering new products and unique designs. Generation Z consumers try to differentiate themselves in terms uniqueness. Lower down the list is the type and degree of interactivity at a LS site: viewers posting messages at a LS site, staff members of the LS site responding to the posted message, and the host responding to some selected viewer messages live in audio and video. Prices being similar to other outlets and no interaction at a LS site are the strongest turn-offs for Generation Z consumers.

The means of standardized best worst scores, as approximations of the underlying relative importance measures, allowed examination of gender differences. Similar to across gender results, lower prices and host characteristics (knowledgeable, entertaining, authentic) are the two most important attributes. Uniqueness of products and designs are also important for both genders but somewhat lower in the list compared to price and host characteristics. The major differences between the two genders are related to the product category they consider engaging. For females (1) clothing and fashion items, and (2) beauty products and cosmetics are more engaging than other product categories whereas for males consumer electronics is more engaging but with a lower best worst score than the scores for females for the two mentioned attributes. Products that are available at other outlets, new products that are similar to existing brands, prices that are similar to prices elsewhere, and no interaction at a LS site are the worst attributes for females. This subset of worst attributes are slightly different for males: new products that are similar to existing brands elsewhere, (1) food and cooking and (2) beauty products and cosmetics

related LS sites as well as no interaction at a LS site are the worst attributes for them.

A second objective of this thesis was to study the general shopping styles of generation Z and examine if they can be instrumental in interpreting the findings of the best worst scaling of the relative importance of the attributes and their levels for a LS site. For this purpose, a subset (29 of the 40) of the items from Sproles and Kendall's (1986) shopping styles questionnaire was administered to the same subjects of the best-worst scaling study. An exploratory factor analysis of the collected data revealed nine factors, seven of which had many variables that loaded on factors similar to the factors reported by Sproles and Kendall (1986). The discovered factors described various shopping styles for consumers who were (1) quality conscious, (2) hedonistic and recreational shoppers, (3) fashion conscious, (4) confused by over choice, (5) brand loyal, (6) impulsive, (7) not price conscious, (8) known brand buyers, and (9) value seekers. Comparison of the related mean factor scores suggested females were more recreational and hedonistic shoppers, more fashion conscious and more confused by over choice. This overall shopping style for females helps explain females' interest in (1) clothing and fashion items and (2) beauty products and cosmetics. Both categories of products include hedonic products that females may take pleasure in and feel emotionally connected. Furthermore, a product category such as clothing and fashion items may include many non-standard unique designs that may confuse the buyer by too many choices. Male generation Z consumers were more interested in buying known brands. This interest is meaningful in the light of the higher importance of electronics for males than females. Relatively more standardized brands and uniform designs for electronics reduce potential confusion by over choice more for males than females who focus on non-uniform more hedonic clothing and fashion items. There were no gender differences for the remaining factors.

Limitations and Future Research

This study needs to be replicated with a bigger sample of respondents and improvements in the best worst scaling approach to demonstrate the reliability of the findings reported here. Also, the findings can be extended to other attributes. Bigger sample size will improve the power of the statistical hypotheses to be tested. Best worst scaling approach can be improved in several directions. Removing price as studied in this study (lower prices versus prices similar to elsewhere) may improve the detection of differences in the importance measures for the remaining attributes and their levels. Since "lower prices" at a LS site is very important for generation Z consumers, it is possible for especially price sensitive respondents to choose "lower prices" at a LS site as the best attribute in multiple profiles of a BWS questionnaire. This may eliminate the opportunity to indicate other positive (good) attributes as the best in their responses. A pilot test where price is replaced by another attribute can shed light on this issue. Note that this case of very important attribute for the majority of the respondents is different than the attribute dominance that is discussed in the discrete choice literature (Bliemer et al., 2017; Bliemer & Rose, 2011) and recently in Case 2 BWS (Soekhai et al., 2021). In that context, an

attribute is dominant when all its levels are preferred over all levels of every other attribute.

Another limitation of the BWS2 used in this study is the assumption that all respondents will be able to attend to all attributes and their levels. Also, the respondents will be able to discriminate between various levels of attributes (for example, what the difference would be between a host who is knowledgeable and entertaining and another host who is both knowledgeable and entertaining but at the same time authentic). Such "lack of discrimination" across the attributes and their levels for the respondents and "attribute non-attendance" across the respondents of BWS2 remains unexplored (Lagerkvist et al., 2012) but they are expected to affect the results in complicated ways. This is likely to be a limitation especially in this study where some respondents did not have prior experiences with LS. To control for "attribute non-attendance" and "lack of discrimination" extensions of BWS2 such as Relevant Items MaxDiff and Anchored MaxDiff (Orme, 2019) can be considered. Relevant Items MaxDiff focuses on items that are relevant to each respondent. Anchored MaxDiff asks questions to determine if items (alternative and their levels) included in BWS are important and liked in an absolute sense (Orme, 2019). A potential difficulty of applying the Relevant Items MaxDiff and Anchored MaxDiff is that these approaches are available as a component of commercial software (Sawtooth Software).

Heterogeneity of the BWS judgements was studied only with respect to gender. However, sophisticated statistical models such as latent class analysis, mixed logit analysis and hierarchical Bayesian analysis are available to capture the nature of heterogeneity for segmentation purposes (Allenby et al., 1998; Kamakura & Russel, 1989; Sarrias & Daziano, 2017). Latent class analysis was attempted in this study. However, the results for two latent classed generated very large logit coefficients for the second latent class and convergence problems despite multiple starts to avoid any estimation problems. Estimation of logit coefficients for three or more latent classes was not possible.

A limitation of the factor analysis related to shopping styles was that it included only 29 of the 40 items that appeared in the original study (Sproles & Kendall, 1986) because of concerns with the combined total survey time for BWS and shopping styles. For this reason, a confirmatory factor analysis using the factor structure reported by Sproles and Kendall (1986) for comparison was not attempted. Future attempt to measure shopping styles should update the questionnaire to reflect shopping related to new forms of retailing on the internet, social media and a combination of "brick-and-mortar" stores with social media possibly extending coverage to virtual reality and use of avatars. If the shopping styles questionnaire is updated so that it is relevant for LS, the factors that can be identified may be useful in interpreting the relative attractiveness of LS attributes. Also, with large enough samples measurement invariance properties of the shopping styles questionnaire can be tested across relevant groups such as genders. Factor means can then be estimated as a part of the measurement model rather than relying on estimated factor scores that may be affected by the rotation of the factor loadings matrix.

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APPENDIX 1: PART 1 QUESTIONNAIRE – BEST-WORST SCALING

INTRODUCTION AND CONSENT FORM
You are being invited to participate in the research study mentioned above. Please read this consent form carefully before deciding if you want to participate or not. If there is anything you do not understand, or if you want more information, please email the researcher.

A. PURPOSE
The purpose of the research is to determine consumer preferences for attributes of Live Stream Online Shopping for your generation (Generation Z).

B. PROCEDURES
If you participate, you will be asked to view a short presentation supported by video and images of live stream shopping. Next, you will review descriptions of various live stream shopping outlets. For each outlet, you will choose the best and the worst characteristic for you if you planned to engage in a live stream shopping session at that web outlet. In total, participating in this study will take about 30 minutes.

C. RISKS AND BENEFITS
There are no risks associated with this study to you. The benefits are likely to be indirect: the findings are expected to be used as general guidelines for designing live stream shopping sites that will meet the needs and wants of consumers, namely your generation.

D. CONFIDENTIALITY
We will use the information you provide only for the purposes of the research described in this form. The information gathered will be strictly confidential. We will not allow anyone to access the information that you provide, except people directly involved in conducting the research. We intend to publish the results of the research. However, it will not be possible to identify you in the published results. We will destroy the information five years after the end of the study.

F. CONDITIONS OF PARTICIPATION
This is a two-part study. You are examining Part 1 right now. It takes about 30 minutes and you will be given 1 credit in MRP if you participate. You need to have taken Part 1 to be able to take Part 2. It also takes about 30 minutes for 1 MRP credit. You can take Part 2 a week after taking Part 1.

You do not have to participate in this research. It is purely your decision. If you do participate, you can stop at any time. You can also ask that the information you provided not be used, and your choice will be respected There are no negative consequences for not participating, stopping in the middle, or asking us not to use your information. Note that once the survey is submitted, responses cannot be withdrawn

G. PARTICIPANT'S DECLARATION

I have read and understood this form. I have had the chance to ask questions by email to the researcher. I know that I can stop at any time in this online survey without any negative consequences.

If you have questions about the scientific or scholarly aspects of this research, please contact the researcher. Their contact information is on page 1. You may also contact her faculty supervisor. If you have concerns about ethical issues in this research, please contact the Manager, Research Ethics, Concordia University, 514.848.2424 ex. 7481 or oor.ethics@concordia.ca.

Do you agree to participate in this survey under the conditions described?

○   I agree to participate in this research under the conditions described

○   I do not agree to participate in this research under the conditions described.

$$\boxed{\rightarrow}$$

Live Stream Online Shopping has been extremely successful, for example in China, raising expectations about a similar strong trend in North America especially with the young generation. First, we will present **short videos** and some **images** to describe Live Stream Online Shopping in case you may not have engaged with such sites.

Please click blue box on the lower right corner to continue.

$$\boxed{\rightarrow}$$

The Evolution of Taobao Live:

Please click in the center of the following image. Not in the lower left corner. When the video ends click on the blue box in the lower right corner to continue.
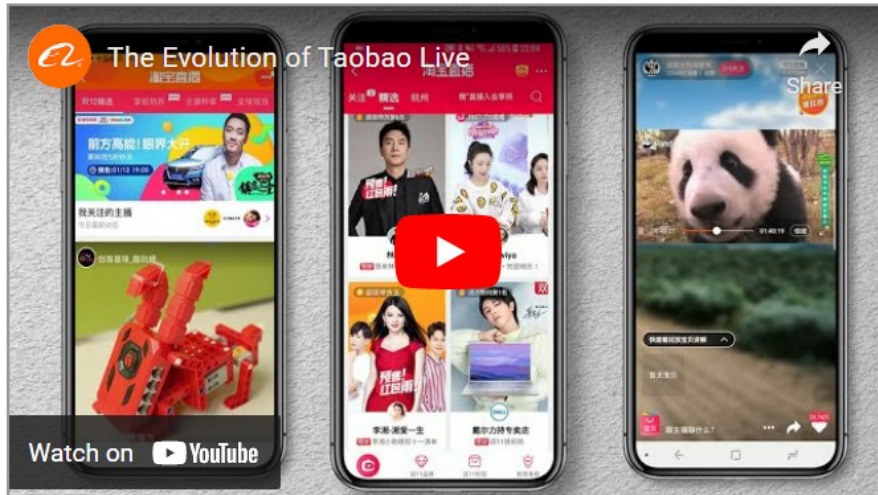
What is live video shopping?

Please click in the center of the following image. Not in the lower left corner. When the video ends click on the blue box in the lower right corner to continue.

Examples of live stream online shopping in North America.
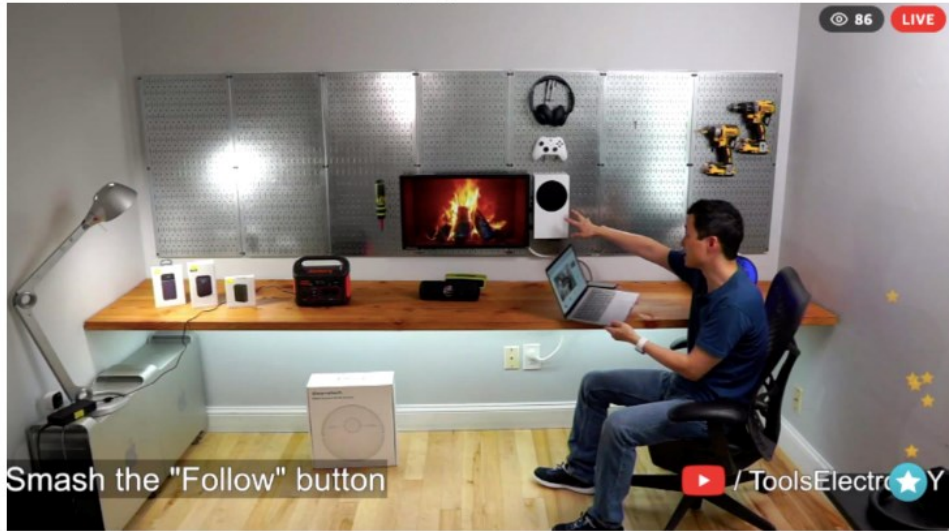
Tools. Electro. DIY is a part of the Amazon Influencer Program

Featured now		
Soundcore by Anker Life Q30 Hybrid Active Noi...	Anker Soundcore Liberty Air 2 Pro True Wireless...	eufy Security Solo IndoorCam P24, 2K Pa...
$79.99	$99.99	$51.99

→

Examples of live stream online shopping in North America.

Black Stripes is a part of the Amazon Influencer Program

Featured now		
Tapata Women's 26"/28"/30" Skinny...	Hybrid & Company Super Comfy Stretch...	Signature by Levi Strauss & Co. Gold Lab...
$32.99	$26.19	$26.79

→

Examples of live stream online shopping in North America.

ImpartialGeek is a part of the Amazon Influencer Program

Featured now Microwave Bacon Cooker - The Original Makin... $13.99	Fat Trapper System/Grease Storag... $23.97	amazon live Watch more livestreams See more

→

Examples of live stream online shopping in North America.
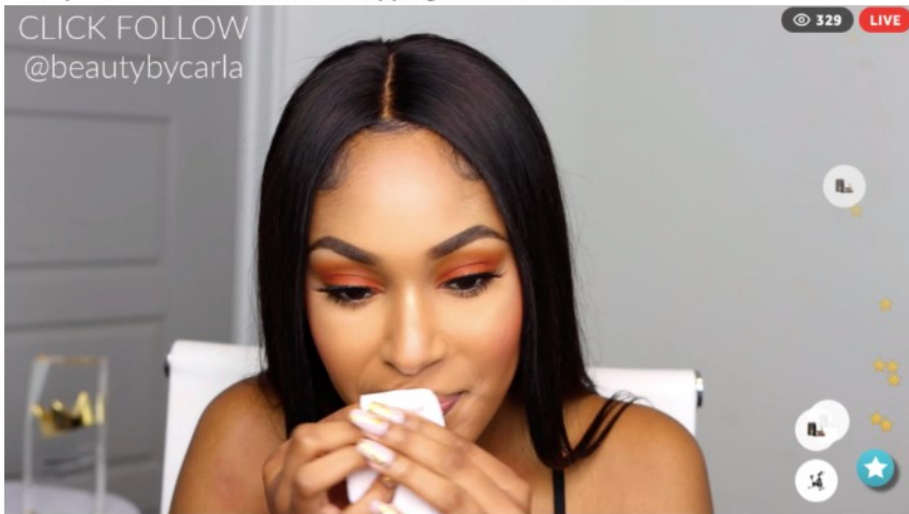
BEAUTYBYCARLA is a part of the Amazon Influencer Program

Featured now Milani Color Statement Matte Lipstick - Matte... $4.97	bareMinerals Barepro Performance Wear... $23.99	SHW 55-Inch Large Electric Height... $288.87

→

Which attributes (characteristics or features) of Live Stream Online Shopping would be more attractive to you if you considered engaging with such an outlet in social media? Engagement in the current context may include the following: viewing the presentations and demonstrations by a host, and possibly interacting by texting and/or calling the site staff and the host on the phone, and buying a product/service.

Consumers' likelihood of engaging with a Live Stream Shopping Outlet seems to be affected by some attributes (characteristics or features) of the outlet. Some of the attributes are: (1) the characteristics of the **HOST**, (2) **PRICES** at the site, (3) nature of **INTERACTIVITY** offered at the site, (4) categories of **PRODUCTS** marketed, (5) the **BRANDS**, models and their uniqueness.

Remaining questions have a common format. For each question, a Live Stream Online Shopping outlet will be described in terms the above mentioned five attributes. For each outlet, you will simply indicate which of these attributes would be the **BEST** and which one would be the **WORST** attribute for you if you considered engaging with this site.
For example, in the following question the respondent thinks "prices lower than competition" is the **BEST** attribute and "marketing of new brands with similar designs available elsewhere" is the **WORST** attribute of the outlet.

Best Attribute		Worst Attribute
○	HOST: entertaining	○
●	PRICES: lower than competition	○
○	INTERACTION: Watch, buy.	○
○	PRODUCTS: consumer electronics	○
○	BRANDS: new brands, similar designs elsewhere	●

→

Q1. A Live Stream Online Shopping outlet is described below. Please read the description carefully. Indicate which of these attributes would be the BEST and which one would be the WORST attribute for you if you considered engaging with this site.

Best Attribute		Worst Attribute
O	HOST: entertaining	O
O	PRICES: similar to competition	O
O	INTERACTION: Watch, leave comments, may get invited to a live video discussion with the host, buy.	O
O	PRODUCTS: food, cooking	O
O	BRANDS: known brands, marketed also elsewhere	O

Q2. A Live Stream Online Shopping outlet is described below. Please read the description carefully. Indicate which of these attributes would be the BEST and which one would be the WORST attribute for you if you considered engaging with this site.

Best Attribute		Worst Attribute
O	HOST: knowledgeable and entertaining	O
O	PRICES: similar to competition	O
O	INTERACTION: Watch, leave comments which are selectively displayed live, buy.	O
O	PRODUCTS: consumer electronics	O
O	BRANDS: known brands, marketed also elsewhere	O

Q3. A Live Stream Online Shopping outlet is described below. Please read the description carefully. Indicate which of these attributes would be the BEST and which one would be the WORST attribute for you if you considered engaging with this site.

Best Attribute		Worst Attribute
○	HOST: knowledgeable, entertaining and authentic	○
○	PRICES: similar to competition	○
○	INTERACTION: Watch, buy	○
○	PRODUCTS: food, cooking	○
○	BRANDS: known brands, unique designs	○

Q4. A Live Stream Online Shopping outlet is described below. Please read the description carefully. Indicate which of these attributes would be the BEST and which one would be the WORST attribute for you if you considered engaging with this site.

Best Attribute		Worst Attribute
○	HOST: knowledgeable, entertaining and authentic	○
○	PRICES: similar to competition	○
○	INTERACTION: Watch, leave comments which are selectively displayed live, buy.	○
○	PRODUCTS: beauty products, cosmetics	○
○	BRANDS: new brands, similar designs elsewhere	○

Q5. A Live Stream Online Shopping outlet is described below. Please read the description carefully. Indicate which of these attributes would be the BEST and which one would be the WORST attribute for you if you considered engaging with this site.

Best Attribute		Worst Attribute
○	HOST: knowledgeable	○
○	PRICES: similar to competition	○
○	INTERACTION:Watch, leave comments, may get invited to a live video discussion with the host, buy.	○
○	PRODUCTS: clothing, fashion	○
○	BRANDS: new brands, similar designs elsewhere	○

Q6. A Live Stream Online Shopping outlet is described below. Please read the description carefully. Indicate which of these attributes would be the BEST and which one would be the WORST attribute for you if you considered engaging with this site.

Best Attribute		Worst Attribute
○	HOST: knowledgeable, entertaining and authentic	○
○	PRICES: lower than competition	○
○	INTERACTION: Watch, leave comments, may get invited to a live video discussion with the host, buy.	○
○	PRODUCTS: consumer electronics	○
○	BRANDS: new brands, unique designs	○

Q7.A Live Stream Online Shopping outlet is described below. Please read the description carefully. Indicate which of these attributes would be the BEST and which one would be the WORST attribute for you if you considered engaging with this site.

Best Attribute		Worst Attribute
○	HOST: knowledgeable	○
○	PRICES: lower than competition	○
○	INTERACTION: Watch, leave comments which are selectively displayed live, buy.	○
○	PRODUCTS: food, cooking	○
○	BRANDS: new brands, unique designs	○

Q8. A Live Stream Online Shopping outlet is described below. Please read the description carefully. Indicate which of these attributes would be the BEST and which one would be the WORST attribute for you if you considered engaging with this site.

Best Attribute		Worst Attribute
○	HOST: knowledgeable, entertaining and authentic	○
○	PRICES: lower than competition	○
○	INTERACTION: Watch, leave comments which are selectively replied live, buy	○
○	PRODUCTS: clothing, fashion	○
○	BRANDS: known brands, marketed also elsewhere	○

Q9.A Live Stream Online Shopping outlet is described below. Please read the description carefully. Indicate which of these attributes would be the BEST and which one would be the WORST attribute for you if you considered engaging with this site.

Best Attribute		Worst Attribute
○	HOST: entertaining	○
○	PRICES: lower than competition	○
○	INTERACTION: Watch, buy.	○
○	PRODUCTS: consumer electronics	○
○	BRANDS: new brands, similar designs elsewhere	○

Q10. A Live Stream Online Shopping outlet is described below. Please read the description carefully. Indicate which of these attributes would be the BEST and which one would be the WORST attribute for you if you considered engaging with this site.

Best Attribute		Worst Attribute
○	HOST: knowledgeable	○
○	PRICES: similar to competition	○
○	INTERACTION: Watch, leave comments which are selectively replied live, buy	○
○	PRODUCTS: consumer electronics	○
○	BRANDS: known brands, unique designs	○

Q11. A Live Stream Online Shopping outlet is described below. Please read the description carefully. Indicate which of these attributes would be the BEST and which one would be the WORST attribute for you if you considered engaging with this site.

Best Attribute		Worst Attribute
O	HOST: entertaining	O
O	PRICES: similar to competition	O
O	INTERACTION: Watch, leave comments which are selectively replied live, buy	O
O	PRODUCTS: beauty products, cosmetics	O
O	BRANDS: new brands, unique designs	O

Q12. A Live Stream Online Shopping outlet is described below. Please read the description carefully. Indicate which of these attributes would be the BEST and which one would be the WORST attribute for you if you considered engaging with this site.

Best Attribute		Worst Attribute
O	HOST: entertaining	O
O	PRICES: lower than competition	O
O	INTERACTION: Watch, leave comments which are selectively displayed live, buy.	O
O	PRODUCTS: clothing, fashion	O
O	BRANDS: known brands, unique designs	O

Q13. A Live Stream Online Shopping outlet is described below. Please read the description carefully. Indicate which of these attributes would be the BEST and which one would be the WORST attribute for you if you considered engaging with this site.

Best Attribute		Worst Attribute
○	HOST: knowledgeable and entertaining	○
○	PRICES: lower than competition	○
○	INTERACTION: Watch, leave comments which are selectively replied live, buy	○
○	PRODUCTS: food, cooking	○
○	BRANDS: new brands, similar designs elsewhere	○

Q14. A Live Stream Online Shopping outlet is described below. Please read the description carefully. Indicate which of these attributes would be the BEST and which one would be the WORST attribute for you if you considered engaging with this site.

Best Attribute		Worst Attribute
○	HOST: knowledgeable and entertaining	○
○	PRICES: lower than competition	○
○	INTERACTION: Watch, leave comments, may get invited to a live video discussion with the host, buy.	○
○	PRODUCTS: beauty products, cosmetics	○
○	BRANDS: known brands, unique designs	○

Q15. A Live Stream Online Shopping outlet is described below. Please read the description carefully. Indicate which of these attributes would be the BEST and which one would be the WORST attribute for you if you considered engaging with this site.

Best Attribute		Worst Attribute
○	HOST: knowledgeable and entertaining	○
○	PRICES: similar to competition	○
○	INTERACTION: Watch, buy.	○
○	PRODUCTS: clothing, fashion	○
○	BRANDS: new brands, unique designs	○

Q16. A Live Stream Online Shopping outlet is described below. Please read the description carefully. Indicate which of these attributes would be the BEST and which one would be the WORST attribute for you if you considered engaging with this site.

Best Attribute		Worst Attribute
○	HOST: knowledgeable	○
○	PRICES: lower than competition	○
○	INTERACTION:Watch, buy.	○
○	PRODUCTS: beauty products, cosmetics	○
○	BRANDS: known brands, marketed also elsewhere	○

→

Were you born between 1997 and 2006?

Yes

No

Please indicate the gender identity that best describes you at the present time

Male

Female

Other

Prefer not to say

Please enter you student ID.

→

APPENDIX 2: PART 2 QUESTIONNAIRE – SHOPPING STYLES

INTRODUCTION AND CONSENT FORM

You are being invited to participate in the research study mentioned above. Please read this consent form carefully before deciding if you want to participate or not. If there is anything you do not understand, or if you want more information, please email the researcher.

A. PURPOSE

The purpose of this research is to determine how consumers engage with the marketplace and alternative products/services whey they shop and make purchasing decisions.

B. PROCEDURES

If you participate, you will simply express how much you agree or disagree with a number of shopping and decision-making related statements. In total, participating in this study will take 30 minutes.

C. RISKS AND BENEFITS

There are no risks associated with this study to you. This research is not intended to benefit you personally.

D. CONFIDENTIALITY

We will use the information you provide only for the purposes of the research described in this form. The information gathered will be strictly confidential. We will not allow anyone to access the information that you provide, except people directly involved in conducting the research. We intend to publish the results of the research. However, it will not be possible to identify you in the published results. We will destroy the information five years after the end of the study.

F. CONDITIONS OF PARTICIPATION

This is the second part of a two part study. You are examining Part 2 right now. You need to have completed Part 1 before this part. It takes about 30 minutes to complete. You will be given 1 credit for your participation.

You do not have to participate in this research. It is purely your decision. If you do participate, you can stop at any time. You can also ask that the information you provided not be used, and your choice will be respected There are no negative consequences for not participating, stopping in the middle, or asking us not to use your information. You do not have to participate in this research. It is purely your decision. If you do participate, you can stop at any time. You can also ask that the information you provided not be used, and your choice will be respected There are no negative consequences for not participating, stopping in the middle, or asking us not to use your information. Note that once the survey is submitted, responses cannot be withdrawn

G. PARTICIPANT'S DECLARATION

I have read and understood this form. I have had the chance to ask questions by email to the researcher and any questions have been answered. I know that I can stop at any time in this online survey without any negative consequences.

If you have questions about the scientific or scholarly aspects of this research, please contact the researcher. Their contact information is on page 1. You may also contact her faculty supervisor. If you have concerns about ethical issues in this research, please contact the Manager, Research Ethics, Concordia University, 514.848.2424 ex. 7481 or oor.ethics@concordia.ca.

Do you agree to participate in this survey under the conditions described?

○ I agree to participate in this research under the conditions described

○ I do not agree to participate in this research under the conditions described.

→

Q1 The following are some statements regarding shopping and decision making by consumers. Please read the statement on the left carefully and then rate how strongly you agree or disagree with it by clicking on the corresponding button.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I am impulsive when purchasing.	○	○	○	○	○	○	○

Q2 Please read the statement on the left carefully and then rate how strongly you agree or disagree with it by clicking on the corresponding button.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I keep my wardrobe up-to-date with the changing fashions.	○	○	○	○	○	○	○

Q3 Please read the statement on the left carefully and then rate how strongly you agree or disagree with it by clicking on the corresponding button.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
Often I make careless purchases I later wish I had not.	○	○	○	○	○	○	○

Q4 Please read the statement on the left carefully and then rate how strongly you agree or disagree with it by clicking on the corresponding button.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
High quality department and specialty stores offer me the best products.	○	○	○	○	○	○	○

Q5 Please read the statement on the left carefully and then rate how strongly you agree or disagree with it by clicking on the corresponding button.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I should plan my shopping more carefully than I do.	○	○	○	○	○	○	○

Q6 Please read the statement on the left carefully and then rate how strongly you agree or disagree with it by clicking on the corresponding button.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
Shopping is one of the enjoyable activities of my life.	○	○	○	○	○	○	○

Q7 Please read the statement on the left carefully and then rate how strongly you agree or disagree with it by clicking on the corresponding button.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
Sometimes it's hard to choose where to shop.	○	○	○	○	○	○	○

Q8 Please read the statement on the left carefully and then rate how strongly you agree or disagree with it by clicking on the corresponding button.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
When it comes to purchasing products, I try to get the very best or perfect choice.	○	○	○	○	○	○	○

Q9 Please read the statement on the left carefully and then rate how strongly you agree or disagree with it by clicking on the corresponding button.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
The lower price products are usually my choice.	○	○	○	○	○	○	○

Q10 Please read the statement on the left carefully and then rate how strongly you agree or disagree with it by clicking on the corresponding button.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I usually have one or more outfits of the very newest style.	○	○	○	○	○	○	○

Q11 Please read the statement on the left carefully and then rate how strongly you agree or disagree with it by clicking on the corresponding button.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
The more I learn about products, the harder it seems to choose the best.	○	○	○	○	○	○	○

Q12 Please read the statement on the left carefully and then rate how strongly you agree or disagree with it by clicking on the corresponding button.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
The well-known national brands are best for me.	○	○	○	○	○	○	○

Q13 Please read the statement on the left carefully and then rate how strongly you agree or disagree with it by clicking on the corresponding button.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
To get variety, I shop different stores and choose different brands	O	O	O	O	O	O	O

Q14 Please read the statement on the left carefully and then rate how strongly you agree or disagree with it by clicking on the corresponding button.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
Fashionable, attractive styling is very important to me.	O	O	O	O	O	O	O

Q15 Please read the statement on the left carefully and then rate how strongly you agree or disagree with it by clicking on the corresponding button.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
The more expensive brands are usually my choices.	O	O	O	O	O	O	O

Q16 Please read the statement on the left carefully and then rate how strongly you agree or disagree with it by clicking on the corresponding button.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
Shopping is not a pleasant activity to me.	O	O	O	O	O	O	O

Q17 Please read the statement on the left carefully and then rate how strongly you agree or disagree with it by clicking on the corresponding button.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
Shopping wastes my time.	○	○	○	○	○	○	○

Q18 Please read the statement on the left carefully and then rate how strongly you agree or disagree with it by clicking on the corresponding button.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
Getting very good quality is very important to me.	○	○	○	○	○	○	○

Q19 Please read the statement on the left carefully and then rate how strongly you agree or disagree with it by clicking on the corresponding button.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I prefer buying the best-selling brands.	○	○	○	○	○	○	○

Q20 Please read the statement on the left carefully and then rate how strongly you agree or disagree with it by clicking on the corresponding button.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I enjoy shopping just for the fun of it.	○	○	○	○	○	○	○

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Q21 Please read the statement on the left carefully and then rate how strongly you agree or disagree with it by clicking on the corresponding button.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I buy as much as possible at sale prices.	○	○	○	○	○	○	○

Q22 Please read the statement on the left carefully and then rate how strongly you agree or disagree with it by clicking on the corresponding button.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I change brands I buy often.	○	○	○	○	○	○	○

Q23 Please read the statement on the left carefully and then rate how strongly you agree or disagree with it by clicking on the corresponding button.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
My standards and expectations for products I buy are very high.	○	○	○	○	○	○	○

Q24 Please read the statement on the left carefully and then rate how strongly you agree or disagree with it by clicking on the corresponding button.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
Once I find a product or brand I like, I buy it regularly.	○	○	○	○	○	○	○

Q25 Please read the statement on the left carefully and then rate how strongly you agree or disagree with it by clicking on the corresponding button.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
There are so many brands to choose from that often I feel confused.	○	○	○	○	○	○	○

Q26 Please read the statement on the left carefully and then rate how strongly you agree or disagree with it by clicking on the corresponding button.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I take the time to shop carefully for best buys.	○	○	○	○	○	○	○

Q27 Please read the statement on the left carefully and then rate how strongly you agree or disagree with it by clicking on the corresponding button.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
In general, I usually try to buy the best overall quality.	○	○	○	○	○	○	○

Q28 Please read the statement on the left carefully and then rate how strongly you agree or disagree with it by clicking on the corresponding button.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
All the information I get on different products confuses me.	○	○	○	○	○	○	○

Q29 Please read the statement on the left carefully and then rate how strongly you agree or disagree with it by clicking on the corresponding button.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I go to the same retail outlets each time I shop.	○	○	○	○	○	○	○

Q30 Please read the statement on the left carefully and then rate how strongly you agree or disagree with it by clicking on the corresponding button.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I look carefully to find the best value for the money.	○	○	○	○	○	○	○

Q31 Please read the statement on the left carefully and then rate how strongly you agree or disagree with it by clicking on the corresponding button.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I have favorite brands I buy over and over.	○	○	○	○	○	○	○

→

Were you born between 1997 and 2006?

Yes

No

Please indicate the gender identity that best describes you at the present time

Male

Female

Other

Prefer not to say

Please enter you student ID.

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