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Consumer personality and lifestyles at the box office and beyond: How demographics, lifestyles and personalities predict movie consumption

Anthony Palomba

College of Professional Studies, St. John's University, United States

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ABSTRACT

While movie studios have leveraged data traditionally through demographics, there may be missed opportunities in securing further granular insights through personality and lifestyle scales. Due to the amount of hyper-competition among movies but also across platforms, marketers and advertisers may revisit consideration of how consumer personality and consumer lifestyle may aid them in predicting movie frequency consumption across genres and platforms. This study deployed a survey and collected a national randomized sample (N=301). Implications include cultivating consumer profiles and anticipating how certain personalities and lifestyles may help measure certain movie genre and movie platform consumption.

"What the studios need to do is start embracing the front end of the business…to start knowing who their customers are, and to start building mechanisms to communicate with them, and tell them when their new product is coming out…[selling films] is going to get a lot more interesting, more precise, cheaper, [and] efficient" – Steve Jobs at a 2010 digital conference (Rainey, 2016).

1. Introduction

Capturing information on movie audiences has never been easier for marketers and advertisers. With the advent of streaming video on demand apps such as Netflix, Hulu, and HBO, these companies are able to harness reams of data not just to understand movie consumption, but to also excavate latent consumer psychological links between themselves and movie consumption, as well as craft well-designed strategic communication toward targeted movie consumer profiles. Although it is currently struggling to pave a financial future for itself, MoviePass has illustrated the possibility of tracking in-house movie theater consumption beyond tracing purchases at movie concession stands (Spangler, 2019). AMC Stubs, Cinemark Connections, and Regal Entertainment Group's Crown Club are other loyalty membership cards that reward consumers who attend movies at movie theaters and collate movie consumption data. To sign up for AMC Stubs A-list, consumer names, email addresses, home addresses, and age are included (AMC Theaters, 2018). To sign up for Cinemark Connections, only consumer emails, phone numbers, zip codes, and names are collected (Cinemark, 2018). From these two movie websites, it appears as though that some of these movie theater companies have averted opportunities to learn more personal information about consumers, including perceptions of their personalities and lifestyles, and exploit these metrics for refined movie consumption prediction models.

Consumer personalities and lifestyles can denote media preferences, but are not always accounted for by marketers and academics. In truth, data capture and analyses are proprietary in nature and are not made available for public consumption, and there is scant academic literature surrounding the types of metrics used in big data collection surrounding movie consumption. A study by Villani (1975) found that in predicting television show consumption, measuring for personality alone explained 2–8% of variance, measuring for lifestyle alone explained 7–17% of variance, and measuring for demographics alone explained 0–6% of variance. However, together, these measurements were able to explain 8–21% variance surrounding television show viewing. Moreover, Lin (2002) recommends employing multi-segmentation approaches to help identify niche and target sub-markets to discover competitive advantages.

While these measurements may have been less relevant amid fewer entertainment brands competing in the 1970s, there are now dozens of entertainment distribution and content brands (e.g. Warner Bros., Netflix, Disney, Lionsgate, and CBS). Additionally, there are highly visible franchise brands that are so popular that they function as their own enterprise and may be found on multiple distribution networks (e.g. *Big Bang Theory*, *Breaking Bad*, *Mad Men*, and *The Office*). This same

E-mail address: apalomba87@gmail.com.

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phenomenon is also found in movie theaters, as film franchises like *Transformers* and *Fast and Furious* debut in movie theaters, but with tremendous distribution alacrity are made available elsewhere. The number of exhibited movies have increased in the past few years, from 602 movies released in 2011 to 740 released in 2017 (Box Office Mojo: Yearly Box Office, 2018). This has placed even more pressure on movie studio executives to increase movie advertising budgets in fear of missing advertising opportunities to consumers across available platforms. This is due to a knowledge gap suffered by many movie studios in that they do not or are in the process of learning how to collect consumption data points to formulate consumer profiles (Rainey, 2016). As a result, it is up to them to race to advertise in as many spaces as possible to as many consumers as possible to enflame buzz around a movie. Hyper-competition among movies means that having the ability to account for all facets of the consumer profile may mean the difference between being profitable and being a box office flop. To offset rising advertising costs, and even cut them down, it is necessary to spend advertising dollars conservatively and wisely toward consumers with similar backgrounds, tastes, and preferences.

According to Rubin (2009), past studies have also demonstrated that understanding how consumers select media is largely based on a) individual differences (e.g. demographics and lifestyles), b) program characteristics (e.g. genre preferences and consumption frequencies), c) media habits/preferences (e.g. platform preferences and consumption frequencies) and d) cognitive and affect elements (psychographics). This exploratory study endeavors to incorporate demographics, psychographics, and lifestyles to gather a sense of how reliable these elements are together to predict movie frequency consumption and movie platform frequency consumption among frequent movie consumers.

This study begins with a theoretical inquiry to weave together diffusion of innovations theory and trait theory. A literature review follows offering arguments to study the aforementioned variables. Multiple linear regressions are run to further understand how frequent movie consumers' demographic, psychographic, and lifestyle information may predict individual movie genre frequency consumption and movie platform frequency consumption. After consideration of the results, a structural equation model is run to consider how aggregate demographic, lifestyle, and personality may be related to aggregate movie genre frequency consumption and movie platform frequency consumption across frequent movie consumers.

2. Movie consumption

In examining the annual MPAA theater statistics report for 2019, it is ostensibly clear that traditional movie consumption has become a fractured enterprise, as consumers view movies not just on movie screens, but through tablets, smartphones, television screens, desktops, laptops and video game consoles. The movie theater industry accrued nearly \$41.1 billion dollars (\$29.2 billion dollars from international movie theaters) in 2018, which was a 1% increase from 2017 (MPAA, 2019). Nearly 75% of consumers living in the United States and Canada went to the movie theaters at least once in 2018. There has been a 33% increase in subscriptions among movie goers to streaming-video-on-demand (SVOD) services. Consumers view movies on numerous screens, as spending on digital home media increased by 24% from 2017, and frequent movie goers (those who attend the cinema at least once a month) are inclined to own video game consoles and video streaming devices, often owning four or more types of technology (MPAA, 2019).

Frequent movie goers are savvy media users who are inclined to adopt technology and view movies, and are the key sample focus in this study. Finally, these consumers make numerous movie consumption decisions across genres and platforms, and are therefore poised to have made a multitude of consumption decisions. They are likely inclined to subscribe to SVOD services, and own multiple types of technologies. From this, it follows that they are driven to adopt and master technology, which likely impacts the contours of their lifestyles. The portability of entertainment offers them more control over their entertainment experiences, and empowers them to shop around for other entertainment experiences.

The decision to use a particular platform, be it a smart phone or a laptop, are likely informed by consumers' socio-economic states and their own natural proclivities toward lifestyle activities. A study by Nielsen (2019) that examined diverse consumers and platform use found several insights that are related to this study. Women use smartphones and tablets significantly more than men. African-Americans, Hispanic-Americans, and Asian-Americans were found to use smartphones more than the overall United States adult average. African-Americans led all ethnic groups in smartphone usage, and Asian-Americans are inclined to use tablets. Logically, it follows that particularly busy, technology-adoption focused, or luxurious lifestyles may lend themselves toward owning more portable platforms, as tablets and smartphones are more portable than flat screen television sets. A study by Tan et al. (2018) illustrate that extraverted consumers are inclined to use smartphones social application use more so than neurotic consumers. Personality may dictate not just frequency of platform consumption, but type of platform adoption, too.

RQ1: Across frequent movie consumers, how do demographics, lifestyles, and personalities predict individual movie platform frequency consumption?

3. Diffusion of innovation

Consumers may shift the types of platforms and windows they use to consume movies based on their interest in using new technology. The rate of new technology adoption is best explained through diffusion of innovation theory (Rogers, 2003). Interest in adopting new technology may skew toward those who are younger with more available income to spend (Rogers, 2003). It is often reliant on the advantage of current innovations, compatibility, complexity, ability to experiment with technology, and observability (Rogers, 2003). This spectrum of technology adoption ranges from innovators, who are most likely to adopt technology despite risk through laggards, who are most hesitant to adopt technology. The largest portions of adoption usually involve early majority and late majority consumers (Goldsmith and Flynn, 1992). While this theory is not being directly tested here, it functions as a conceptual basis in understanding how rate of new technology adoption figures into movie consumption.

Numerous media studies in the past have examined how media platform adoption may impact consumption of media. Dispersion of identical content across media platforms leads to simultaneous competition across platforms, otherwise known as cannibalization of content (Shay, 2015). Consumers may consider other available media platforms if they are useful and different from other platforms in nature (Chan-Olmsted and Shay, 2016). Twitter has been found to be adopted by journalists based on pressure from colleagues and its perceived use in garnering and galvanizing followers to engage with journalists and share news stories (Swasy, 2016). Consumer profitability may oscillate across diffusion of innovation, as different consumer segments may be targeted with unique strategic communication. Understanding platform use, and consumer biases toward certain ones, will aid movie marketers in effectively monetizing and optimizing use of each available window to exhibit movies on (Sood and Kumar, 2017). Since movie studios have discussed same-day release of movies across all platforms in the future, it is necessary to investigate consumer penchants toward being the first to view a movie. From there, we can begin to assess how they leverage media repertoires to optimize movie consumption experiences. Interest in adopting new technology may be tied to consumer personality, since a willingness to try new products and services necessitates a high level of openness and risk-taking.

3.1. Trait theory & personality

A consumer's rate of interest in adopting new products and services is affirmed in part through their individual personality composition. Personality has been conceptualized as a cadre of behavioral points along a behavioral spectrum that agglomerate onto traits, engendering distinct personality types (Pervin,1989). Traits connote fixed variance in consumer behavior across a wide variety of social contexts and situations. Most scholars assume that there is little to moderate vacillation within these traits, and that these traits can be quantified (Eysenck and Eysenck, 1985; Shim and Paul, 2007). The study of personality traits is part of a larger study surrounding the study of internal emotional and conceptual mechanisms within consumers. Psychographics may serve as a supplement to understand market segmentation, as it incorporates sociological, psychological, and anthropological elements to figure out how a market is segmented, and this may be based on services, products, people, or belief systems (Solomon, 2015). Latent psychological characteristics, such as personality and lifestyle patterns, can help educate marketers on the routinized behaviors of consumers (Plummer, 1974).

Personality has been found to be predictive or correlated alongside media consumption in the past. Psychographic segmentation can provide additional, if not better, information than demographics (Lin, 2002). Another study by Sandy et al. (2013) found that personality provided greater predictive integrity than demographics in television show consumption. Personality was able to explain 3% of variance in movies consumed in theaters per month. A meta-study conducted by Hoffner and Levine (2005) demonstrated that sensation-seeking and imagination predicted horror affinity and frequency consumption. Krcmar and Kean (2005) illustrated that neuroticism was related to viewing violent media and crime content, though admittedly there was no relationship between neuroticism and enjoying the aforementioned content.

4. Demographics

While personality traits can shed light on products and services that consumers consume, this variable alone paints an inchoate picture. Demographics can often help marketers create ready-made groupings based on income, ethnicity, age, gender, education, and political affiliation. Consumer demographics serve as the baseline for most advertising and marketing campaigns, and are often used to place consumers into segments (Solomon, 2015). Demographics have been used to illuminate different media consumption types and frequencies (Guo and Chan-Olmsted, 2015; Kim, 2017; Villani, 1975).

Demographics are an important precursor toward understanding how movie longevity and frequency consumption is understood. Consumer behavior patterns may be highlighted in part by these measurements. Most frequent movie consumers are 25–39 years old (11.1%) and 40–49 years old (6.8%). Additionally, 23% of frequent movie goers identified as Caucasian followed by 10% who identified as Hispanic-Americans (MPAA, 2019). Hispanic-Americans were more inclined to visit movie theaters (4.7 times per year) compared to Asian-Americans (4.5 times a year), African-Americans (3.7 times a year), and Caucasians (3.3 times per year).

Demographics may serve as a way in which to better understand how movies may appeal to particular consumer segments, and how their consumption patterns alter over a movie product life cycle during a movie theater run. For instance, during *Star Wars: The Force Awakens* movie campaign run, the opening night crowd was 72% male, but fell to 61% by the following Thursday. Age is another relevant metric here, as with the *Jurassic World* movie campaign run, 15–30 year olds made up roughly 22% of the total audience, though it was closer to 34% on its opening night (Ault, 2016). Clearly, much can be garnered from demographics in laying out a well-crafted marketing campaign to push for more females or older audience members to attend a movie, as they are the slowest demographic to subside in attendance during a theatrical run (Ault, 2016). Demographics clearly have an impact on movie platform frequency consumption and movie genre frequency consumption. Gender may help determine when consumers may consume a movie during its theatrical run, and race/ethnicity may aid in understanding frequency of movie platform use (Ault, 2016; Nielsen, 2019). This type of behavior is informed in part by consumer lifestyles, which underscore what consumers enjoy doing during their leisure time.

4.1. Lifestyle

Different from most demographic traits that are inherited, lifestyle instruments allow for capturing information about what activities consumers engage in. The multitude of lifestyle segment scales produced have been used to connect marketers to consumers, such as the activities, interests, opinions (AIO) (Plummer, 1974) rating scale and the value, attitude, and lifestyles (VALS) scale (Mitchell, 1983). The AIO scale employs several hundred questions investigating consumer lifestyle. While this scale offers a thorough examination of consumers' lifestyles, it is difficult to carry out given the quantity of questions in it. The VALS questionnaire is useful, since it examines consumers' values through their lifestyles. However, this scale is not terribly varied in the amount or type of consumer activities it lists. Another lifestyle scale, created by Green et al. (2006), accounts for a variety of lifestyle activities, including whether consumers eat out in restaurants and take vacations through a thirty-six item scale. Lifestyle scales have demonstrated to serve as a link in holistic understanding in consumer values and brand preferences (Orth et al., 2004).

Unearthing consumer lifestyles allows for deep inquiry into the types of platforms consumers use to view media, since this is predicated in part on interest to adopt technology (Rogers, 2003), as well as content selection preferences. Consumer lifestyles fluctuate across age groups, particularly among younger consumer segments who seek out customizable experiences that offer novelty and cultural capital, such as entertainment (Weinberger et al., 2017). This is linked to platforms, as they range in size, scope, and level of immersion. It is also associated with genre, as selection of entertainment content may be preempted by consideration of genre first.

4.2. Genres

The lifestyles that consumers lead may be tangentially related to their genre preferences. A genre is an organized set of expectations, styles, or elements within an artform. For instance, in a romance comedy, there may be love, teasing, and jocular behavior between two lovers as well as involvement from over-the-top best friends and other points that are indicative of the genre itself. This is just as useful for consumers as it is for movie advertising practitioners, as it is important for them to be able to manage consumer expectations surrounding viewing a movie. Genres are often one of the first items consumers consider when selecting a movie (Austin and Gordon, 1987).

Since genres are one of the first pieces of information considered when making a movie decision, demographic metrics including age and ethnicity should be factored here, as it has been previously established in this study. Consumer personality has been found to influence selection in music genre, as neurotic consumers were inclined to listen to pop-rock music, and psychotic consumers were less inclined to watch romance and comedy films (Hall, 2005). Extraversion has also been found to be associated with reality television programming (Shim and Paul, 2007). Gender has been linked to movie preferences, though consumer perception may over exaggerate the differences between both genders (Wuhr et al., 2017). Lifestyle has been illustrated to serve as a key metric for movie consumer segmentation, illustrating strong consumer variation across cultural attendance, reading, learning new languages, as well as demographic variables including age, gender, and employment status (Diaz et al., 2018). Although it is not tested here, social identity theory states that consumers have a sense of who they are based on what they perceive themselves to belong to, which may include a social class, a football team, or other activity-based groups they identify with (Tajfel, 1979). Consumer activities may be linked to genres that depict what they do during their leisure, as well as what they aspire to be.

RQ2: Across frequent movie consumers, how do demographics, lifestyles, and personalities predict individual movie genre frequency consumption?

5. Method

5.1. Demographics

To measure for demographics, age, gender, education, location, household income, and political affiliation were used here. Based on a study by Kim (2017), this study used a set of demographic questions, including a political ideology scale from the General Social Survey (Smith et al., 2017). Ordinal scales were used to measure education and political affiliation. Gender and race/ethnicity were measured on categorical scales. Finally, age was measured on an interval scale. Location was measured by consumers stating their state and zip code.

5.2. Platform

To measure for platform use, consumers were asked how often they used certain media platforms to view movies. Some of the indicators included laptop computer, desktop computer, cable TV, Satellite TV, and video game console. This 11-item Likert scale ranged from 1=Never to 5=Always.

5.3. Innovation scale

To measure for innovation, a scale developed by Goldsmith and Flynn (1992) was used here. This scale was selected because it considers consumer interests to own and purchase new products and services compared to their group of friends. This is an effective scale to measure diffusion of innovation (Rogers, 2003) since it takes into consideration not only consumers' rate of adoption, but also their awareness of it compared to their friends. Some of the indicators included "If I heard that a new movie was available for purchase, I would be interested enough to buy it," "Compared to my friends, I own few new movies," and "In general, I am the last in my circle of friends to know the names of the latest movies." This 5-item Likert scale ranged from 1=Strongly Disagree to 5=Strongly Agree.

5.4. Genre preference

To measure genre preferences, a list of thirteen genres was created based on the Internet movie database (IMDB) (Guo and Chan-Olmsted, 2015). The list of genres included science fiction, horror, romance, comedy, action, drama, thriller, mystery, crime, animation, adventure, fantasy, and superhero. This 13-item Likert scale ranged from 1=Never Watch to 5=Watch All The Time.

5.5. Personality

To measure for personality, a scale by Oliver and Srivastava (1999) was used here. This scale was used since it was a shorter personality scale in nature, and asked consumers to reflect upon who they saw themselves as. Some of the indicators included "I see myself as someone who is talkative," "I see myself as someone who is relaxed, handles stress well," and "I see myself as someone who generates a lot of enthusiasm." This 44-item Likert scale ranged from 1=Strongly Disagree to 5=Strongly Agree.

5.6. Lifestyle

To measure for lifestyle, a combination of a recreation scale developed by Green et al. (2006) and lifestyle scale by Mitchell (1983) were used here. These two scales were used since the recreation scale was shorter than other lifestyle scales, and the Mitchell (1983) scale also offered indicators surrounding values. Several of the indicators included "commute more than 45 min to work every workday," "watch sports on television," and "read nature, wildlife, or environmental magazines." This 45-item Likert scale ranged from 1=Never to 5=Always.

5.7. Data collection

To fund pursuit of this study, a CUNY research grant was won. The researcher applied for and gained IRB approval. Afterwards, a survey-pretest was conducted on Amazon Mechanical Turk, securing a non-randomized sample of one hundred participants (n=100). The results illustrated good variation in answer choices, and participants understood the language used in the survey. A final survey was deployed through Qualtrics to a national randomized sample of movie consumers. Qualtrics is a data collection firm that relies on a consumer panel and randomly selects participants who are likely to qualify to participate in research studies (Qualtrics, 2019). Qualtrics compensates participants after participation in each research study. This study was interested in consumers who viewed movies, and so consumers needed to view at least one movie per week to be incorporated into the study. This was done in part based on the Motion Picture Association of America's (2019) definition for frequent movie consumer, but to also ensure that these consumers who took the survey consumed movies across numerous genres and platforms. After data-cleaning, there were three hundred and one (N=301) participants remaining for further data analyses.

6. Results

Participant gender was roughly even, as 48.7% of participants were male. Participant age was fairly dispersed across all life stages, including 18–27 years old (21%), 28–37 years old (17.7%), 38–47 years old (15.3%), 48–57 years old (17%), 58–67 years old (17.7%), and 68 years old and over (11.3%). 37% of participants earned incomes of $60,000 or more. Across race and ethnicity, the participant sample included Caucasians (65.30%), African-Americans (12.70%), Asian-Americans (6%), Hispanic-Americans (18%), and mixed/other ethnicities (2%). Through political orthodoxy, participants identified as extremely liberal (7.7%), liberal (12.30%), slightly liberal (9.70%), moderate (28.30%), slightly conservative (12.30%), and conservative (20.70%) (Table 1).

To conduct further statistical analyses with lifestyle and personality variables, several exploratory factor analyses were conducted with varimax rotations. This was done to maximize explanatory power while reducing the amount of indicators necessary to do so (Hair et al., 2010). A principle component factor analysis was run for consumer lifestyles, and the KMO score was 0.936, and the Bartlett's Test of Sphericity was statistically significant ($p<.001$) (Table 2). For the first lifestyle scale, Travel and Business ($\alpha=.86$), the indicators included "Travel by air for business purposes" (0.69), "Live somewhere else three or more months out of the year" (0.69), "Commute more than 45 min to work every work day" (0.68), "Work at home or 'telecommute'" (0.67), and "Operate your own independent business" (0.65). For the second factor, Indulge ($\alpha=.73$), the indicators included "Eat out in restaurants, including fast food, or order take-out food at least 2 times a week" (0.64), "Attend movies at the theater 1 or more times a month" (0.60), "Purchase items online" (0.56), "Take vacations away from home at least once a year" (0.55), and "Get together socially with friends or neighbors" (0.54). For the third factor, Informed ($\alpha=.80$), the indicators included "Read magazines" (0.73), "Read news, business, or professional magazines" (0.70), and "Read newspapers" (0.68).

Table 1
Demographics.

	Frequency	Valid Percent	Cumulative Percent
Gender			
Male	146	48.70%	
Female	154	51.30%	100%
Age			
18-27	63	21%	
28-37	53	17.7%	38.70%
38-47	46	15.3%	54%
48-57	51	17%	71%
58-67	53	17.7%	88.70%
68+	34	11.3%	100%
Education			
Less than high school graduate	9	3%	
High school graduate	69	23%	26%
Some college but no degree	76	25.30%	51.30%
Associate degree in college (2-year)	42	14%	65.30%
Bachelor's degree in college (4-year)	61	20.30%	85.60%
Master's degree	27	9%	94.60%
Doctoral degree/Professional degree (JD, MD)	5	1.70%	96.30%
Household Income			
Less than $10,000	27	9%	
$10,000 to $19,999	20	6.70%	15.70%
$20,000 to $29,999	29	9.70%	25.40%
$30,000 to $39,999	40	13.30%	38.70%
$40,000 to $49,999	22	7.30%	46.00%
$50,000 to $59,999	40	13.30%	59.30%
$60,000 to $69,000	24	8%	67.30%
$70,000 to $79,999	22	7.30%	74.60%
$80,000 to $89,999	8	2.70%	77.30%
$90,000 to $99,999	15	5.00%	82.30%
$100,000 to $149,999	32	10.70%	93%
$150,000 or more	10	3.30%	96.30%
Ethnicity			
Caucasian	196	65.30%	
African Americans	38	12.70%	78%
Asian-Americans	18	6%	84%
Hispanic-Americans	54	18%	102%
Mixed/Other	6	2%	104%
Political Identity			
Extremely Liberal	23	7.70%	
Liberal	37	12.30%	20%
Slightly liberal	29	9.70%	29.70%
Moderate, middle of the road	85	28.30%	58%
Slightly conservative	37	12.30%	70.30%
Conservative	62	20.70%	91%

Table 2
Factor analysis of lifestyle.

Factors	1	2	3
Factor 1: Travel and Business (α=.86)			
Travel by air for business purposes	0.69		
Live somewhere else three or more months out of the year	0.69		
Commute more than 45 min to work every workday	0.68		
Work at home or 'telecommute'	0.67		
Operate your own independent business	0.65		
Factor 2: Indulge (α=.73)			
Eat out at restaurants, including fast food, or order take-out food at least 2 times a week		0.64	
Attend movies at the theater 1 or more times a month		0.60	
Purchase items online		0.56	
Take vacations away from home at least once a year		0.55	
Get together socially with friends or neighbors		0.54	
Factor 3: Informed(α=.80)			
Reading magazines			0.73
Read news, business, or professional magazines			0.70
Read newspapers			0.68
Eigenvalues	14.99	2.83	2.18
% of total variance accounted for	33.31	6.28	4.85

A principle component factor analysis was run for consumer personalities, and the KMO score was 0.871 and the Bartlett's Test of Sphericity was statistically significant ($p<.001$) (Table 3). For the first factor, Unfocused (α=.80), the indicators included "Tense" (0.72), "Depressed" (0.71), "Careless" (0.71), "Lazy" (0.71), and "Easily Distracted" (0.68). For the second factor, Reliable (α=.77), the indicators included "Forgiving" (0.69), "Trusting" (0.68), "Considerate" (0.66), "Cooperate" (0.64), and "Helpful and Unselfish" (0.57). For the third factor, Inventive (α=.76), the indicators included "Inventive" (0.71), "Original Ideas" (0.70), "Active Imagination" (0.65), "Deep Thinker" (0.64), and "Reflect" (0.53).

Initially, the location variable was run in the hierarchical regressions model, but quickly became problematic as a variable that possessed multicollinearity. Correlations were run with genre frequency to understand general patterns between movie genre frequency consumption and location. Consumers in the northeast were less inclined to view thriller-based movies ($\beta= -.13$, $p<.03$), consumers in the south were disinclined to frequently view animated movies ($\beta= -.14$, $p<.02$), consumers in the west were inclined to view animation ($\beta=.15$, $p<.01$), and consumers in the midwest were disinclined to view super hero movies ($\beta= -.15$, $p<.01$). For platform frequency use, consumers in the northeast were inclined to own Smart TVs ($\beta=.13$, $p<.03$). There were no correlations between movie frequency and location. This metric was subsequently dropped, as it appeared to not predict much explained variance.

To examine how demographics, lifestyles, and personalities impact movie genre frequency consumption, multiple linear regressions were run (Table 4). To predict comedy frequency consumption ($F=3.44$, $p<.001$), notable predictors included African-American ($\beta= -.17$, $p<.05$), age ($\beta= -.25$, $p<.001$), sex (females) ($\beta=.16$, $p<.05$), and personality-inventive ($\beta=.17$, $p<.01$). To predict science fiction frequency consumption ($F=3.59$, $p<.001$), notable predictors included income ($\beta=-.20$, $p<.01$), education ($\beta=.14$, $p<.05$), sex (males) ($\beta= -.17$, $p<.01$), and personality-unfocused ($\beta=.16$, $p<.05$). To predict horror frequency consumption ($F=3.73$, $p<.001$), notable indicators included lifestyle-business ($\beta=.18$, $p<.05$) and lifestyle-innovation ($\beta=.18$, $p<.01$). To predict romance frequency consumption ($F=3.95$, $p<.001$), notable predictors included Caucasian ($\beta= -.22$, $p<.05$), sex (females) ($\beta=.16$, $p<.05$), and lifestyle-informed ($\beta=.24$, $p<.01$). To predict action frequency consumption ($F=1.87$, $p<.02$), notable indicators included political affiliation (conservative) ($\beta=.13$, $p<.05$), and lifestyle-innovation ($\beta=.14$, $p<.05$). To predictor thriller frequency consumption ($F=1.72$, $p<.05$), notable predictors included sex (males) ($\beta= -.16$, $p<.05$), and personality-reliable ($\beta=.16$, $p<.05$).

Table 3
Factor analysis of personality.

Factors	1	2	3
Factor 1: Unfocused (α=.80)			
Tense	0.72		
Depressed	0.71		
Careless	0.71		
Lazy	0.71		
Easily Distracted	0.68		
Factor 2: Reliable (α=.77)			
Forgiving		0.69	
Trusting		0.68	
Considerate		0.66	
Cooperate		0.64	
Helpful and Unselfish		0.57	
Factor 3: Inventive (α=.76)			
Inventive			0.71
Original Ideas			0.70
Active Imagination			0.65
Deep Thinker			0.64
Reflect			0.53
Eigenvalues	8.45	6.06	2.96
% of total variance accounted for	19.2	13.77	6.72

Table 4
Impact of demos, lifestyle and personality on comedy, science fiction, horror, and romance movie genre consumption frequencies.

	Comedy		Science Fiction		Horror		Romance		Action		Thriller	
	β	S.E.	β	S.E.	β	S.E.	β	S.E.	β	S.E.	β	S.E.
Caucasian	-.02	(-.26)	.09	(-.27)	-.11	(-.30)	-.22*	(.26)	-.12	(-.25)	-.05	(-.27)
African-American	*-0.17	(-.32)	-.09	(-.34)	-.16	(-.38)	-.10	(.32)	-.11	(-.31)	-.04	(-.33)
Asian or Asian-American	-.08	(-.37)	.07	(-.4)	-.12	(-.44)	-.05	(.37)	-.07	(-.36)	.01	(-.39)
Hispanic or Hispanic-American	-.04	(-.27)	-.04	(-.29)	-.08	(-.32)	.00	(.27)	.05	(-.26)	-.01	(-.28)
Income	-.01	(-.02)	-.20**	(-.03)	-.06	(-.03)	-.04	(.02)	-.06	(-.02)	-.04	(-.03)
Political Affiliation	-.05	(-.05)	-.04	(-.05)	-.05	(-.06)	.00	(.05)	.13*	(-.05)	.04	(-.05)
Education	.03	(-.06)	.14*	(-.06)	-.11	(-.07)	.03	(.06)	.08	(-.05)	-.03	(-.06)
Age	-.25**	(-.01)	-.13	(-.01)	-.11	(-.01)	-.07	(.01)	.07	(-.01)	-.01	(-.01)
Sex	.16*	(-.15)	-.17**	(-.16)	.05	(-.18)	.16*	(.15)	-.12	(-.15)	-.16*	(-.16)
Lifestyle- Travel Business	-.08	(-.09)	.10	(-.10)	.18*	(-.11)	-.02	(.09)	-.03	(-.09)	-.05	(-.01)
Lifestyle - Indulgence	.08	(-.11)	.09	(-.12)	-.03	(-.13)	.09	(.11)	.08	(-.11)	.13	(-.11)
Lifestyle - Informed	.02	(-.09)	-.15	(-.09)	.06	(-.10)	.24**	(.09)	-.07	(-.08)	-.01	(-.09)
Lifestyle - Innovation	.00	(-.11)	.12	(-.12)	.18**	(-.13)	.07	(.11)	.14*	(-.11)	.09	-.12
Personality - Reliable	.09	(-.09)	.09	(-.10)	.02	(-.11)	.09	(.09)	.09	(-.09)	.16*	(-.09)
Personality - Unfocused	.12	(-.12)	.16*	(-.12)	-.03	(-.14)	.11	(.12)	.07	(-.11)	.01	(-.12)
Personality - Inventive	.17**	(-.10)	.10	(-.11)	.11	(-.12)	-.09	(.10)	.07	(-.10)	.11	(-.11)
F	3.44		3.59		3.73		3.95		1.87		1.72	
R	0.42		0.43		0.44		0.45		0.32		0.31	
R^2	0.13		0.13		0.14		0.15		0.05		0.04	
Sig. of Model	p<.001		p<.001		p<.001		p<.001		p<.02		p<.04	

*=p<.05.
**=p<.01.
***=p<.001.

In continuing the examination of how demographics, lifestyles, and personalities impact movie genre frequency consumption multiple linear regressions were run (Table 5). To predict drama frequency consumption (F=2.26, p<.01), a notable predictor was lifestyle-indulgence (β=.23, p<.01). There were no predictors for mystery frequency consumption. To predict crime frequency consumption (F=2.67, p<.001), notable predictors included political affiliation (conservative) (β=.15, p<.05), and lifestyle-innovation (β=.17, p<.05). To predict animation frequency consumption (F=4.00, p<.001), notable predictors included age (β= -.32, p<.001), and personality-unfocused (β=.17, p<.05). To predict adventure frequency consumption (F=3.56, p<.001), sex (male) (β= -.20, p<.01), lifestyle-indulgence (β=.17, p<.05), lifestyle-innovation (β=.13, p<.05), and personality-unfocused (β=.23, p<.001). To predict fantasy frequency consumption (F=2.29, p<.001), a notable predictor was personality-inventive (β=.14, p<.05) and personality-reliable (β=.16, p<.05). To predict super hero frequency consumption (F=4.39, p<.001), notable predictors include age (β= .30, p<.001), sex (male) (β= -.17, p<.01), lifestyle-innovation (β=.19, p<.01), personality-reliable (β=.14, p<.05) and personality-unfocused (β=.23, p<.001).

To examine how demographics, lifestyles, and personalities predict movie frequency platform consumption, multiple linear regressions were run (Table 6). To predict cable TV frequency consumption (F=1.83, p<.03), notable predictors included African-American (β=.33, p<.001) and Hispanic or Hispanic-American (β=.21, p<.05). To predict satellite TV frequency consumption (F=2.84, p<.001) a notable

Table 5
Impact of demos, lifestyle and personality on drama, mystery, crime, animation, adventure, fantasy, and superhero.

	Drama		Mystery		Crime		Animation		Adventure		Fantasy		Superhero	
	β	S.E.	β	S.E.	β	S.E.	β	S.E.	β	S.E.	β	S.E.	β	S.E.
Caucasian	.16	(0.24)	.07	(0.24)	.18	(0.25)	-.04	(0.28)	.07	(0.23)	-.13	(0.26)	.07	(0.27)
African-American	.09	(0.29)	.13	(0.30)	.12	(0.31)	-.04	(0.35)	.02	(0.28)	-.06	(0.32)	.04	(0.34)
Asian or Asian-American	.02	(0.34)	.04	(0.35)	.06	(0.37)	-.09	(0.40)	.01	(0.33)	-.02	(0.38)	.05	(0.39)
Hispanic or Hispanic-American	.00	(0.25)	.01	(0.25)	.13	(0.26)	-.01	(0.29)	-.02	(0.24)	-.14	(0.27)	.08	(0.28)
Income	.05	(0.02)	-.05	(0.02)	-.09	(0.02)	-.05	(0.03)	-.01	(0.02)	-.02	(0.02)	-.06	(0.03)
Political Affiliation	-.03	(0.05)	.02	(0.05)	.15*	(0.05)	-.06	(0.05)	.09	(0.04)	.00	(0.05)	.04	(0.05)
Education	.03	(0.05)	.02	(0.05)	.05	(0.06)	.02	(0.06)	.02	(0.05)	-.02	(0.06)	.11	(0.06)
Age	.07	(0.01)	.05	(0.01)	.03	(0.01)	-.32***	(0.01)	-.10	(0.01)	-.07	(0.01)	-.30***	(0.01)
Sex	.04	(0.14)	-.02	(0.14)	-.02	(0.15)	-.01	(0.17)	-.20**	(0.14)	-.06	(0.16)	-.17**	(0.16)
Lifestyle- Travel Business	-.12	(0.09)	-.03	(0.09)	-.12	(0.09)	.01	(0.10)	-.06	(0.08)	.02	(0.10)	-.10	(0.10)
Lifestyle - Indulgence	.23**	(0.1)	.13	(0.10)	.14	(0.11)	-.01	(0.12)	.17*	(0.10)	.11	(0.11)	.13	(0.12)
Lifestyle - Informed	.08	(0.08)	.11	(0.08)	.09	0.08)	.05	(0.09)	-.04	(0.08)	-.05	(0.09)	-.06	(0.09)
Lifestyle - Innovation	.02	(0.10)	.06	(0.10)	.17*	(0.11)	.10	(0.12)	.13*	(0.10)	.09	(0.11)	.19**	(0.12)
Personality - Reliable	.11	(0.08)	.05	(0.08)	.11	(0.09)	.13	(0.10)	.05	(0.08)	0.16*	(0.09)	.14*	(0.10)
Personality - Unfocused	.07	(0.11)	.14	(0.11)	.12	(0.11)	.17*	(0.13)	.23***	(0.10)	.04	(0.12)	.23***	(0.12)
Personality - Inventive	.02	(0.01)	.07	(0.10)	.05	(0.10)	.05	(0.11)	.07	(0.09)	0.14*	(0.11)	-.01	(0.11)
F	2.26		2.00		2.67		4.00		3.56		2.29		4.39	
R	0.35		0.33		0.38		0.45		0.43		0.35		0.46	
R^2	0.07		0.06		0.09		0.15		0.13		0.07		0.17	
Sig. of Model	p<.004		p<.02		p<.001		p<.001		p<.001		p<.004		p<.001	

*=p<.05.
**=p<.01.
***=p<.001.

Table 6
Impact of demos, lifestyle and personality on cable TV, satellite TV, SVOD, DVD players, and movie theaters on movie consumption.

	Cable TV		Satellite TV		SVOD		DVD Players		Movie Theaters	
	β	S.E.	β	S.E.	β	S.E.	β	S.E.	β	S.E.
Caucasian	.17	(0.35)	.02	(0.34)	-.08	(0.31)	.30**	(0.30)	.00	(0.65)
African-American	.33***	(0.43)	.03	(0.43)	-0.19*	(0.39)	.18*	(0.37)	.03	(0.73)
Asian or Asian-American	.08	(0.51)	.08	(0.50)	-.01	(0.45)	.11	(0.43)	.19	(1.38)
Hispanic or Hispanic-American	.21*	(0.37)	-.01	(0.36)	-.01	(0.33)	.14	(0.31)	.20	(0.64)
Income	.09	(0.03)	.02	(0.03)	.09	(0.03)	-.10	(0.03)	.01	(0.08)
Political Affiliation	.11	(0.07)	.00	(0.06)	-.06	(0.06)	-.07	(0.06)	-.04	(0.11)
Education	.09	(0.08)	-.08	(0.07)	.00	(0.07)	.00	(0.06)	.05	(0.14)
Age	.03	(0.01)	-.11	(0.01)	-.19*	(0.01)	.00	(0.01)	-.02	(0.02)
Sex	.01	(0.21)	-.07	(0.20)	.15*	(0.19)	.05	(0.18)	.03	(0.42)
Lifestyle- Travel Business	.07	(0.13)	.25**	(0.13)	.05	(0.11)	.14	(0.11)	-.02	(0.28)
Lifestyle - Indulgence	.08	(0.15)	-.03	(0.15)	.23**	(0.13)	.00	(0.13)	.19	(0.28)
Lifestyle - Informed	-.02	(0.12)	.12	(0.11)	-.02	(0.10)	.02	(0.10)	-.16	(0.20)
Lifestyle - Innovation	-.04	.15	.09	(0.15)	.03	(0.14)	.18**	(0.13)	0.43*	(0.31)
Personality - Reliable	.01	.12	-.05	(0.12)	-.06	(0.11)	-.02	(0.10)	.06	(0.25)
Personality - Unfocused	.06	.16	.02	(0.15)	-.04	(0.14)	.13	(0.13)	.05	(0.27)
Personality - Inventive	-.01	.14	.01	(0.14)	.06	(0.13)	-.03	(0.12)	.07	(0.25)
F	1.83		2.84		3.83		2.02		1.93	
R	0.32		0.39		0.44		0.34		0.71	
R^2	0.05		0.15		0.19		0.06		0.24	
Sig. of Model	p<.032		p<.001		p<.001		p<.013		P<.06	

*=p<.05.
**=p<.01.
***=p<.001.

predictor was lifestyle-travel business (β=.25, p<.01). To predict SVOD frequency consumption (F=3.83, p<.001), notable predictors included African-American (β= -.19, p<.05), age (β= -.19, p<.05), sex (female) (β=.15, p<.05), and lifestyle-indulgence (β=.23, p<.01). To predict DVD player frequency consumption (F=2.02, p<.013), notable predictors included Caucasian (β=.30, p<.01), African-American (β=.18, p<.05), and lifestyle-innovation (β=.18, p<.01). To predict once a month movie theater frequency consumption, a notable predictor was lifestyle-innovation (β=.43, p<.05).

To examine how demographics, lifestyles, and personalities predict movie frequency platform consumption, multiple linear regressions were run (Table 7). To predict laptop frequency consumption (F=4.48, p<.001), notable predictors included age (β= -.27, p<.001), and lifestyle-indulgence (β=.17, p<.05). To predict desktop frequency consumption (F=5.18, p<.001), notable predictors included Hispanic or Hispanic-American (β= -.18, p<.05), and lifestyle-travel business (β=.36, p<.001). To predict smartphone frequency consumption (F=7.28, p<.001), notable predictors included age (β= -.21, p<.01), lifestyle-travel and business (β=.23, p<.01), and personality -reliable (β=.14, p<.05). To predict tablet frequency consumption (F=5.49, p<.001), notable predictors included lifestyle-travel and business (β=.25, p<.001), personality-reliable (β=.19, p<.05), and lifestyle-innovation (β=.19, p<.01). To predict video game console frequency consumption (F=8.25, p<.001), notable predictors included age (β= -.31, p<.001), lifestyle-travel business (β=.24, p<.001), and lifestyle-innovation (β=.12, p<.05). To predict Smart TV frequency

Table 7
Impact of demos, lifestyle and personality on laptop, desktop, smartphone, tablet, video game console, and smart TV movie consumption.

	Laptop		Desktop		Smartphone		Tablet		Video Game Console		Smart TV	
	β	S.E.	β	S.E.	β	S.E.	β	S.E.	β	S.E.	β	S.E.
Caucasian	-.15	.30	-.16	(0.29)	-.06	(0.30)	.12	(0.29)	.11	.25	-.02	(0.37)
African-American	-.10	.38	-.04	(0.36)	-.02	(0.37)	.13	(0.36)	.05	.31	-.09	(0.46)
Asian or Asian-American	-.01	.44	-.04	(0.42)	-.01	(0.43)	.08	(0.42)	.10	.37	-.07	(0.53)
Hispanic or Hispanic-American	-.04	.32	-.18*	(0.30)	.10	(0.31)	.11	(0.30)	.00	.26	.05	(0.39)
Income	.00	.03	-.08	(0.03)	.06	(0.03)	-.01	(0.03)	-.02	.02	.06	(0.04)
Political Affiliation	.06	.06	-.01	(0.06)	.04	(0.06)	.03	(0.05)	-.06	.05	.02	(0.07)
Education	-.05	.07	-.07	(0.06)	-.10	(0.06)	-.01	(0.06)	-.03	.05	.02	(0.08)
Age	-.27***	.01	-.03	(0.01)	-.21**	(0.01)	.00	(0.01)	-.31***	.01	-.10	(0.01)
Sex	-.03	.18	-.01	(0.17)	.03	(0.18)	.03	(0.17)	.02	.15	.01	(0.22)
Lifestyle- Travel Business	.14	.11	.36***	(0.11)	.23**	(0.11)	.25***	(0.11)	.24***	.09	.07	(0.13)
Lifestyle - Indulgence	.17*	.13	.07	(0.12)	.12	(0.13)	.02	(0.12)	.00	.11	.13	(0.16)
Lifestyle - Informed	-.04	.10	.04	(0.10)	-.08	(0.10)	.04	(0.10)	.08	.08	.11	(0.12)
Lifestyle - Innovation	-.04	.13	.04	(0.13)	.05	(0.13)	.19**	(0.13)	.12*	.11	.00	(0.16)
Personality - Reliable	.05	.11	.03	(0.10)	.14*	(0.10)	.19**	(0.10)	.07	.09	-.11	(0.13)
Personality - Unfocused	-.03	.14	-.01	(0.13)	.05	(0.13)	.02	(0.13)	.08	.11	-.08	(0.17)
Personality - Inventive	.09	.12	.10	(0.12)	.05	(0.12)	.04	(0.12)	.05	.10	.13*	(0.15)
F	4.48		5.18		7.28		5.49		8.25		2.11	
R	0.47		0.5		0.56		0.51		0.58		0.34	
R^2	0.17		0.2		0.27		0.21		0.3		0.06	
Sig. of Model	p<.001		p<.001		p<.001		p<.001		p<.001		p<.008	

*=p<.05.
**=p<.01.
***=p<.001.

consumption ($F=2.11$, $p<.01$), one notable predictor was personality-inventive ($\beta=.13$, $p<.05$).

6.1. Structural equation model

The multiple linear regressions allowed for individual predictiveness of each movie genre and movie platform as an individually observed variable. However, consumers consider all available movie platforms and genres when making a movie consumption decision. This warrants an investigation into how demographics, personalities, and lifestyles may predict aggregate movie genre frequency consumption and movie platform frequency consumption. Therefore, it was appropriate to test these relationships through a structural equation model (Fig. 1). This statistical tool is built to examine several interrelationships by testing several multiple linear regressions at once (Hair et al., 2010).

To run the structural equation model, observed indicators were used to comprise each latent variable. Based on previous traditional scale and development methods, the results from the factor analyses and coefficient alphas for personality and lifestyle were carried over to the structural equation model. Convergent validity was demonstrated through the statistical significance of the factor loadings alongside composite reliability and divergent validity was examined by considering the variance extracted to the square of the correlation (Anderson and Gerbing, 1988; Bellini et al., 2017). Average variance explained (A.V.E.) and composite reliability (C.R.) scores were calculated and considered alongside Cronbach's alpha scores. Personality was comprised of the unfocused ($\alpha=.80$, A.V.E.$=.50$, C.R.$=.83$), reliable ($\alpha=.77$, A.V.E.$=.42$, C.R.$=.78$), and inventive ($\alpha=.76$, A.V.E.$=.42$, C.R.$=.78$) factors. Lifestyle was comprised of travel and business ($\alpha=.86$, A.V.E.$=.46$, C.R.$=.81$), indulge ($\alpha=.73$, A.V.E.$=.34$, C.R.$=.72$), and informed ($\alpha=.80$, A.V.E.$=.50$, C.R.$=.75$) factors.

The following describes the observed indicators and composite variables used to create the model. Demographics was comprised of household income, political affiliation, education, gender, and race. Movie genre frequency consumption included horror, romance, action, thriller, drama, mystery, crime, adventure, and superhero. Movie platform frequency consumption included laptop computer, desktop computer, smartphone, movie theater (once a month), tablet, video game console, smart TV, cable TV, satellite TV, SVOD, and DVD players. Based on the multiple linear regressions, it appeared that demographics did not predict individual movie genre frequency consumption well, and personality did not predict individual movie platform frequency consumption well. Hence, these relationships were not tested in the structural equation model.

H1. Frequent movie consumers' personalities is a positive predictor of movie genre frequency consumption.

H2. Frequent movie consumers' lifestyles is a positive predictor of movie genre frequency consumption.

H3. Frequent movie consumers' demographics is a positive predictor of movie platform frequency consumption.

H4. Frequent movie consumers' lifestyles is a positive predictor of movie platform frequency consumption.

When consumers make movie consumption decisions, they likely first consider the movie genre from which to select a movie, and are then concerned with selecting a platform on which to view the movie itself. In this vein, consumers are making a genre consumption decision before a

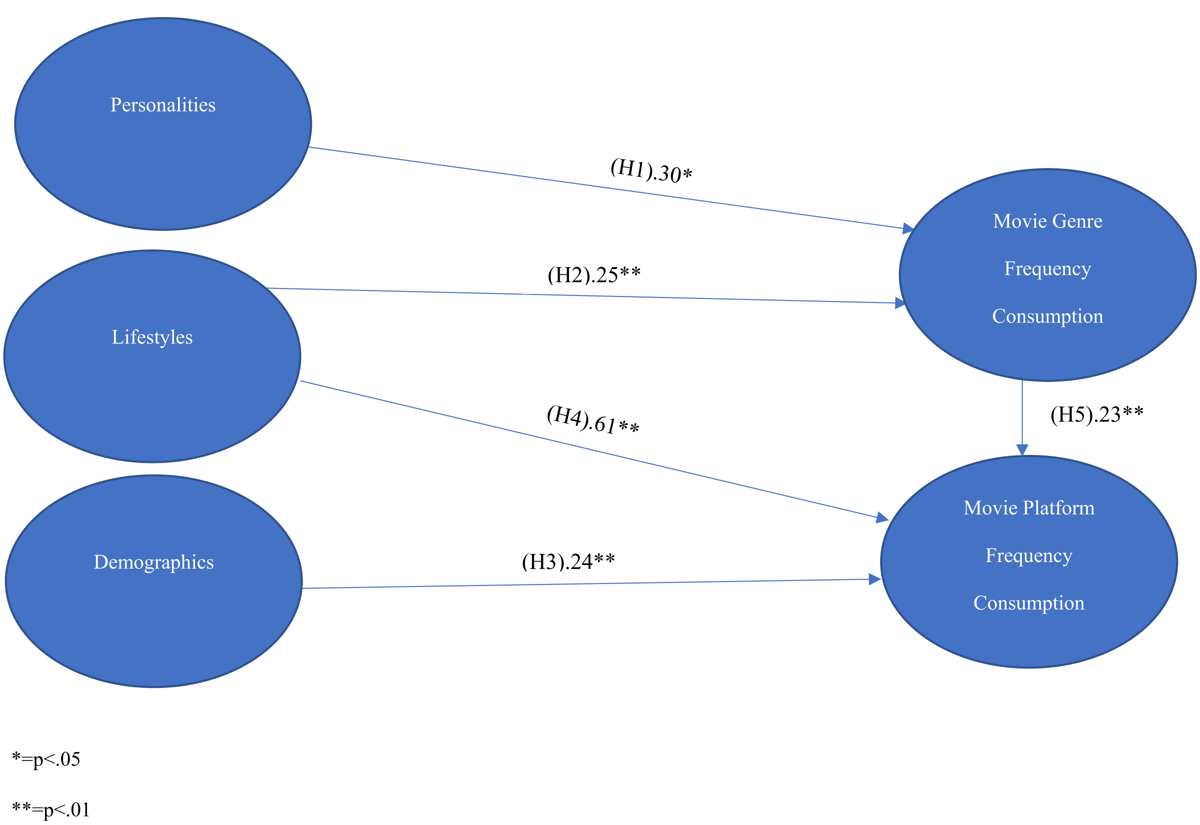

Fig. 1. Structural equation Model
*= $p<.05$,
**= $p<.01$.

platform decision. Therefore, movie genre frequency consumption should be predictive of movie platform frequency consumption.

H5. : Frequent movie consumers' movie genre frequency consumption is a positive predictor of movie platform frequency consumption.

The model produced statistically significant pathways, but the model itself did not precisely fit: X^2=1642.67, df= 551, p <.001, RMSEA=.081, CFI=.589, NFI=.503, PCFI=.518. The statistical significance here indicates that there is a statistically significant difference between the observed and estimated data matrices. The use of chi-square to assess model fit is a thorny inquiry, since it is particularly sensitive at higher sample sizes (Barrett, 2007; Bentler and Bonett, 1980). Sample sizes amplify the discrepancies of the exact-fit test here. Based on this premise, other approximate fit tests as listed above were used to gauge the model fit (Bagozzi and Yi, 1988; Suki, 2011).

Although the model did not precisely fit the data, all tested hypotheses were supported. Personalities was found to be positively predictive toward movie genre frequency consumption (β=.198, p<.045). Lifestyles was found to be positively related toward movie genre frequency consumption (β=.150, p<.003), and movie platform frequency consumption (β=.379, p<.001). Demographics was found to be positively predictive of movie platform frequency consumption (β=.138, p<.026). Finally, movie genre frequency consumption was positively predictive of movie platform frequency consumption (β=.239, p<.005) (Table 9).

7. Discussion

This exploratory study was interested in investigating how consumers' lifestyles, personalities, and demographics may inform how often consumers engage in movie genre frequency consumption, and movie platform frequency consumption. Overall, the findings here indicate that for individual genres and platforms, certain measurements are more useful than others. Through the structural equation model, there is promising evidence that these relationships are statistically significant in an aggregate manner.

Table 8
Coefficients of determination for genre and platform.

	R^2 - Demos	R^2 - Demos + Lifestyle	R^2 - Demos + Lifestyle + Personality
Genre			
Comedy (Freq.)	.07***	.08***	.13***
Science Fi (Freq.)	.07***	.10***	.13***
Horror (Freq.)	.07***	.14***	.14***
Romance (Freq.)	.05**	.14***	.15***
Action (Freq.)	.03	.04*	.05*
Thriller (Freq.)	.003	.02	.04*
Drama (Freq.)	.02	.07**	.07**
Mystery (Freq.)	-.02	.04*	.06*
Crime (Freq.)	.004	.07**	.09***
Animation (Freq.)	.11***	.12***	.15***
Adventure (Freq.)	.03	.08***	.13***
Fantasy (Freq.)	.02	.04*	.07**
Superhero (Freq.)	.08***	.12***	.17***
Platform			
Laptop	.13***	.17***	.17***
Desktop	.04*	.20***	.20***
Smartphone	.19***	.26***	.27***
Tablet	.05**	.19***	.21***
Video Game Console	.19***	.29***	.30***
Smart TV	0.01	.05*	.06*
Cable TV	.06**	.05*	.05*
Satellite TV	.03	.11***	.10***
SVOD	.10***	.15***	.14***
DVD Players	.01	.06**	.06*
Movie Theater	.20*	.29*	.24

*=p<.05.
**=p<.01.
***=p<.001.

The findings surrounding platform and genre use support previous literature on trait theory (Pervin,1989), diffusion of innovation (Rogers, 2003), as well as media selection parameters (Rubin, 2009). Consumer personalities possess enough fixed variation to be predictive, and serve as key performance indicators for movie genre frequency consumption (Pervin, 1989). Consumer personalities were linked to a variety of genres here, illustrating that how consumers perceive their own personalities can help inform which movie genre they select and rate of consumption. Diffusion of innovation is furthered along here in clarifying how consumers use platforms, and which they are most inclined to use to view movies. Clearly, consumers who are interested in being at the forefront of technology adoption are interested in adopting sophisticated platforms, such as Smart TVs, video game consoles, and smartphones (Rogers, 2003). Personalities and lifestyles can also serve as a bellwether for what consumers may be interested in viewing and on what platform as well. They co-exist together, as particular personality traits, including high interests in being inventive or living an informed lifestyle, can open certain activity consideration sets for consumers. Finally, the media choice selection (Rubin, 2009) framework is furthered along as a justifiable and testable model to discover how frequent movie consumers' more controllable (lifestyles) and less controllable (psychographics, genre, platform, and demographics) characteristics can inform their own media preferences. This illustrates the testability of this model, and that it may be applied to other mediums in the future.

Regarding demographic measurements, predictive power was mixed but notable. Through age, it was clear that younger consumers were inclined to view comedy, animation, and superhero movies. Moreover, younger consumers were inclined to smartphones, video game consoles, and use laptops. This extends literature on diffusion of innovation theory, as younger consumers are more inclined to adopt newer platforms to view movies on (Rogers, 2003). Across ethnicities, there was some notable predictions. African-Americans may be disinclined to consume comedy movies, but are inclined to view movies on cable TV, and DVD players. They are also disinclined to view movies on SVOD platforms. Hispanic-Americans are also inclined to view movies in particular on cable TV, and Caucasians were inclined to view movies on DVD players. This supports previous research surrounding platform usage variation across different ethnicities (Nielsen, 2019). Males were inclined to view science fiction, adventure, superhero, and thriller movies, while females were inclined to view romance and use SVOD platforms. This illustrates that gender continues to play a key role in movie genre choice. It cannot be understated how important it is for movie theater and studio executives to continue to collect demographic data.

Finally, as illustrated through demographics, lifestyles, and personalities, there is predictive power in anticipating genre and platform movie consumption frequencies (Table 8) (Villani, 1975). Demographics offer 0–19% predictability, demographics and lifestyle offer 2%–29% predictability, and demographics, lifestyles, and personalities offer 4%–30% predictability. Combined, these measurements offer the most explanatory power for the superhero (R^2=.17), animation (R^2=.15), romance (R^2=.15), horror (R^2=.14), science fiction (R^2=.13), comedy (R^2=.13), and adventure (R^2=.13) movie consumption frequencies. Interestingly, action, thriller, drama, mystery, and fantasy movie consumption frequencies could not be predicted as well. There may be genres that have particularly niche or unique consumer bases who are ardent supporters.

Demographics, lifestyles, and personalities were predictive for some movie platforms more than others. Combined, the aforementioned measurements offered the greatest explanatory power for video game console (R^2=.30), smartphone (R^2=.27), tablet (R^2=.21), desktop (R^2=.20), laptop (R^2=.17), SVOD (R^2=.14), and satellite TV (R^2=.10). It appears as though nuanced and highly specialized platform use may be more predictable than others that are used more ubiquitously, such as

Table 9
Pathway results.

Path			Coefficients	S.E.	C.R.	p-value	Supported/Not Supported
Personalities	→	Movie Genre	.198*	.009	2.007	.045	Supported
Lifestyles	→	Movie Genre	.150**	.051	2.929	.003	Supported
Demographics	→	Movie Platform	.138**	.062	2.224	.026	Supported
Lifestyles	→	Movie Platform	.379**	.081	4.690	.001	Supported
Movie Genre	→	Movie Platform	.239**	.085	2.826	.005	Supported

*=p<.05, **=p<.01.

smart TV or cable TV. Further inquiry is necessary here to determine why there are wide ranges in explanatory power across platform use. This suggests that demographics, lifestyles, and personalities are exceptionally useful to predict certain platforms, but are rapidly less relevant for predicting use on other platforms.

While the structural equation model didn't precisely fit the data, there were several metrics that illustrated near model fit, including the RMSEA and PCFI (Bagozzi and Yi, 1988; Suki, 2011). Still, it is worth noting that all tested hypotheses were supported here. This illustrates that demographics, personalities, and lifestyles are active and precise metrics that can be used to capture explained variance for movie genre and movie platform frequency consumption.

8. Practical implications

Recall that the main inspiration of this paper was to attempt to capture unaccounted for explained variance that is typically not collected by movie theaters or studios. This study illustrates that there may be explained variance available to movie studio executives. It is important for movie marketers and advertisers to become more strategic in collecting personality and lifestyle data points. These data points may be used to predict movie genre and movie platform frequency consumption. It is important to realize the strength and limitations of each measurement, and to also understand how some measurements are more important for predicting certain genres over others. While big data sets may terrorize some marketers and advertisers into sticking to tried and true though antiquated marketing tactics, its enormity may be subdued if data scientists begin to look for alternative measurements that can illuminate movie consumption variation.

The factor analyses executed in this study were adept in creating new personality and lifestyle scales for movie marketers and advertisers to use in evaluating their own audiences. Aside from targeting movies toward audiences, this may aid advertisers and marketers in understanding what types of movie trailers and pre-movie exhibition advertisements might pique the interest and attention spans of audience members. These scales also help illuminate how certain movie consumption behavior may vary together, and that consumers that consume one type of movie may be predisposed to consume other similar movies. For consumers who are lifestyle - business oriented, they are inclined to view horror and satellite TV. For consumers who are lifestyle - indulgence oriented, they are inclined to view dramas and adventure, and use SVOD platforms. By considering frequent movie consumers, and how they may be separated and organized by their personalities and activities, this offers consideration of how this sub-group may function in their day-to-day lives. Across the lifestyle scales, consumers who lead industrious lives, indulge, or are drawn to staying informed seem to have high rates of movie consumption. Across the personality scales, consumers who believe themselves to be reliable, unfocused, or inventive also consume movies at a very high rate. It is useful in identifying these consumers and what they do during the day, as well as how they perceive themselves. This may help illuminate how movie marketers may engage audiences during activities, as well as how to engage them based around their own personalities. It still may be useful to advertise in print media, across luxury items such as at restaurants or around vacation destinations, as well as on planes or places where there are busy commuters.

9. Limitations

There were several key limitations in this study. First, this study focused solely on frequent movie goers, and did not consider mild or casual movie goers. There may be particular consumer patterns across personalities, lifestyles, and demographics that are germane to these consumer segments, which may bear out insights for managers surrounding how to engage them with strategic communication. The structural equation model did not precisely fit the data, and future researchers should consider using alternative variables or scales. Future studies should consider using different psychographic or lifestyle scales to achieve greater model fit. Alternative theory may be considered in order to fortify the underlying theoretical framework that supports this model as well. Different types of factor analyses and structural equation models will yield different fits. While average variance extracted was low here, the Cronbach's alpha scores offered cogent reliability, and there were no major discriminant validity or multicollinearity issues.

10. Future research directions

Future research should center around why consumer personalities are inclined to predict particular movie consumption patterns, as well as how they may be tracked in the future. Further research is necessary to understand why particular ethnicities and genders gravitate toward particular platforms or genres. With the advent of IoT (Internet of Things), artificial intelligence, and other types of smart technology, it may be easier for companies to track and analyze private consumer personalities and lifestyles within households. Firms such as Amazon are doing this, as it possesses reams of consumer data across product verticals, and it presumably exploits this data for its Amazon Prime Video service, creating original series and acquiring content to meet the needs of its subscribers. Researchers may achieve further precision through securing actual data through these instruments. From this study, it is inferred that enhanced tracking of consumer personalities and lifestyles may unearth more insights and solvable questions regarding movie consumption.

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Appendix A. Supplementary data

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