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The Search for Pleasure and Meaning on TV, Captured In-App: *Eudaimonia and Hedonism Effects on TV Consumption as Self-Reported via Mobile App*

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ABSTRACT

The present study investigates the effects of eudaimonia and hedonism on genre preferences by connecting eudaimonia and hedonism survey measures to individuals' self-reported TV-show viewing data over time in the mobile app TV Time. Regression models suggest that higher eudaimonia leads to more viewing of mystery, mini-series, thriller, and drama, but less viewing of family, adventure, and action shows. Higher hedonism leads to more viewing of family, romance, action, and comedy programs, but less viewing of mystery, sci-fi, mini-series, suspense, horror, crime, thriller, and drama shows. Models including hedonism and eudaimonia generally, although not always, fit the data better than demographics-only models.

Though a desire to attain the best or situationally optimal mood was long thought to be the key driver of media preference (e.g., Knobloch, 2003; Knobloch & Zillmann, 2002; Zillmann, 1988), recent research has argued for a two-factor model where the pleasure-seeking hedonic drive is accompanied by a eudaimonic drive that seeks meaning, insight, and self-actualization (e.g., Vorderer, 2011; Vorderer & Reinecke, 2015). Individuals can vary in the extent to which their media consumption is driven by pleasure-seeking or meaning-seeking, and Oliver and Raney (2011) developed hedonism and eudaimonia scales to measure such differences.

However, inquiries into how these two factors together impact media preference remain methodologically limited. The methodology utilized, for example, often involved simultaneous evaluation of eudaimonia, hedonism, and broad genre preference measured on an *n*-point Likert-type scale (e.g.,

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Igartua & Barrios, 2013; Oliver & Raney, 2011), which raised corresponding concerns regarding order effects and hypothesis speculating (McFarland, 1981; Mummolo & Peterson, 2019). In addition, it is important to note that genre liking does not perfectly project onto the implicit behavior of interest in and consumption of media. Fishbein's (2008) integrative model suggests that attitudes such as liking, while important, only explain a certain fraction of variance in behavior, with other central factors such as norms and self-efficacy also playing key roles in predicting behavior.

The present article examines how individuals' eudaimonic and hedonic motivations for entertainment consumption affect genre preferences in TV show consumption, as reported by users in a mobile app that enables individuals to track their TV consumption at the episode-level. Relevant literature on media preferences and self-report mobile apps is reviewed first. These bodies of literature are then synthesized to highlight the limitations of past relevant studies' reliance on using simultaneous survey-based Likert-type measurement scales to assess genre preference, eudaimonia, and hedonism. Then, the manuscript outlines a study connecting a single time-point survey data measuring individuals' eudaimonia and hedonism to TV viewing data self-reported by the same individuals over time in the mobile app TV Time. Regression and likelihood ratio test results are analyzed to examine the effects of eudaimonia and hedonism on the prominence of various genres in users' TV show viewing history and whether the consideration of these factors provides an improvement in fit to the data compared to demographics-only models.

Literature Review

Media Preference, Eudaimonia, Hedonism

Media preference and selective exposure is a key research topic in mass communication research and a necessary precursor to media effects. Studies on the subject often take place in political communication contexts, where it investigates topics such as confirmation-bias style ideological congruence effects (e.g., Coe et al., 2008; Iyengar & Hahn, 2009), or health communication contexts, where content selection can even be an outcome of effects arising from targeting of cues like titles or summaries (e.g., Pease et al., 2006). Though the trait-versus-state-like distinction between high-level preference and in-the-moment selection should be noted (Knobloch-Westerwick, 2015), there is much cross-citing between the related conceptual branches of media preference research.

A long-established, traditional canon of media preference research centers around hedonic considerations, investigating whether people's media choices can be explained by their desire to achieve a positive or otherwise situationally desirable affective state (Knobloch, 2003; Zillmann, 1988). Such mood management effects on selection manifest with a range of formats, having been tested with television (Weaver & Laird, 1995), movies (Strizhakova & Krcmar, 2007), music (Knobloch & Zillmann, 2002), and video games (Bowman & Tamborini, 2015), for example. However, scholars have noted that such hedonic drives may not sufficiently explicate individuals' attraction to sad, less conventionally "pleasurable" media (e.g., Oliver, 2003).

Thus, more recent research has also emphasized a second factor driving media use, suggesting that individuals' media preference is driven by not only by pleasure-seeking, as theories like mood management argue, but also a search for meaning, insight, and self-actualization – a second, *eudaimonic* driver of media use complementing the *hedonic* drive, as investigated by affect-centric theories (Oliver & Raney, 2011; Vorderer, 2011; Vorderer & Reinecke, 2015). The relevance of this second dimension has also been investigated in the context of movies (Oliver & Raney, 2011), books (Koopman, 2015), and video games (Oliver et al., 2016). Studies in this domain have resulted in a push for further research on the broader concept of self-transcendent media experiences, a type of media experience "characterized by feelings of universalism and connectedness, moral virtue and altruism, and spirituality" (p. 386, Oliver et al., 2018).

Oliver and Raney (2011) outlined a six-item scale to measure to what extent individuals' entertainment consumption was driven by such pleasure- (hedonism) or actualization- (eudamonia) seeking motivations. With regard to movies, they found that controlling for gender, higher eudaimonia was associated with increased preference for drama and decreased preference for comedy, among other effects. Higher hedonism was associated with an increased preference for action-adventure and comedy in addition to lower preference for nonfiction. Using a Spanish version of the scale, Igartua and Barrios (2013) reported similar findings, by controlling for gender and age. Their study found hedonism to be positively correlated with preference for action and romance, but negatively correlated with war and history, among other effects. In addition, findings also showed that eudaimonia was positively correlated with preference for drama, political films, and history, but negatively correlated with comedy and action, among other effects. Odağ et al. (2018) suggested that such differences in eudaimonia and hedonism are in part cultural, which alludes to the possibility of eudamonia/hedonism-driven nationality differences in genre preference.

Self-Report Mobile App Data

A popular niche of mobile apps is those enabling users to track behaviors or attitudes through the app interface. Self-reported user data varies depending on context, and academic research has examined such mobile app data in contexts including diet (e.g., Nour et al., 2019), physical health (e.g., Reychav et al., 2019), and beyond.

Data self-reported through these mobile apps[1] can be provided in-situ, by-recall, or a combination of the two (Vaizman, 2018; Vaizman et al., 2018). A prominent benefit of mobile app self-report data is the promise of data non-invasively collected in-situ, close to when a behavior of interest occurred, from users in natural environments. In contrast, by-recall self-report occurs when participants retrospectively evaluate an occurrence in the past, occasionally with some kind of assistive device like photos (e.g., Kahneman et al., 2004; Rabbi et al., 2019).

Despite being relatively new compared to paper-based approaches, extant research suggests the quality of data self-reported via apps is generally similar to that self-reported via more traditional survey methods. Kim et al. (2014) found no difference between the paper- and app-based versions of their physical symptom measure. A literature review conducted by Belisario et al. (2015) suggested that data equivalency between paper- and app-collected data is generally not a concern. However, despite this broad consistency, there may still be user-level variability – for example, Reychav et al. (2019) indicated that with a self-report health app, older patients of 61+ tend to report blood pressure more accurately.

Significance and Research Question

The impact of eudaimonic and hedonic motivations for media consumption, as conceptualized by the Oliver and Raney (2011) measures, on media preferences have only been investigated in limited contexts. Oliver and Raney (2011) revealed that, controlling for gender, their scales are correlated with stated preferences for various genres, as measured on a 7-point scale (ranging from "*not at all*" to "*very much*"). Igartua and Barrios (2013) present similar findings, using a Spanish version of the scale, controlling for gender and age. By measuring genre preference using such scales, one per genre, these studies did not measure actual consumption, but attitudes.

In doing so, hedonism and eudaimonia effects on consumption itself are left to be inferred. Attitude is one of several factors impacting behavior, with models like Fishbein's (2008) integrative model (IM) suggesting that norms and self-efficacy also play a role, such that a positive attitude toward a particular behavior may not necessarily lead to performance of that behavior. This explains, for example, why an individual with a stated preference

[1]The present manuscript recognizes that not all mobile app data is self-reported, with smartphones capable of logging a breadth of data (e.g., Harari et al., 2016); however, for brevity, it uses the term "app" to refer to self-report mobile apps (sometimes called "self-monitoring" apps, e.g., Carter et al., 2017) as detailed above, unless otherwise noted.

for romance movies might not see one due to unfavorable perceived norms surrounding their consumption for someone of their group. Given this imperfect link between attitudes and behavior, it is desirable to measure an action of interest as directly as possible, and in this regard, an app that allows episode-level measurement of consumption is preferable to a survey-based Likert-type measure of liking for certain types of content.

Furthermore, though both surveys and apps as examined in the present manuscript share certain self-report related threats to validity, collecting both predictor and outcome variables in a single survey presents additional concerns regarding participant hypothesis-guessing and order effects (McFarland, 1981; Mummolo & Peterson, 2019). Collecting outcome data via mobile app in a temporally disparate manner relative to the predictor data provides additional methodological rigor by alleviating the validity concerns mentioned above.

The present study builds on the eudaimonia and hedonism-driven genre preference findings from Oliver and Raney (2011) and Igartua and Barrios (2013) to conduct an expanded analysis using a novel data source. Going beyond genre preference as captured on a Likert-type scale, the present study examines proportion values representing the prevalence of various genre shows in participants' viewing history, generated from episode-level, app-based self-reports of TV consumption. These proportions are used as outcome variables in regression models, with users' responses to an abbreviated version of Oliver and Raney (2011) eudaimonic and hedonic motivations for entertainment consumption measures as primary predictors of interest. These models are then compared using likelihood ratio tests against demographics-only models to examine whether their consideration in addition to demographic factors provides a significant improvement in fit.

RQ: How do eudaimonic and hedonic motivations for media consumption impact genre preference in TV show consumption as captured via a self-report mobile app?

Method

Data collection for the present study consisted of two distinct components: 1) measuring eudaimonic motivation (eudaimonia) and hedonic motivations (hedonism) for entertainment consumption via surveys; and 2) accessing each survey respondent's TV viewing history as input into the *TV Time* app. Both the survey data and app data were made available for the present study by Whip Media Group, the developer of the *TV Time* app.

Survey – Abbreviated Eudaimonic and Hedonic Motivation Measure

Four user research surveys unrelated to the present study, two about movies and two about TV shows, were administered to users of the mobile app *TV Time* between 10/28/2019 and 11/11/2019, with users randomly offered the opportunity to participate through an in-app notification that took them to the survey administered on SurveyMonkey. At the conclusion of these surveys, participants were asked to respond to the two highest factor loading items each from the Oliver and Raney (2011) eudaimonia and hedonism scales, four total, in random order; additional items were not included due to fatigue concerns, particularly given the auxiliary nature of the items within the context of the user surveys. The eudaimonia scale measured the extent to which individuals consume entertainment to seek meaning or insight in life, while the hedonism scale measured more typical fun-seeking motivations for consuming media (Oliver & Raney, 2011). The four items of the original 12 were included in the present study and answered on a 7-point scale (*strongly disagree – strongly agree*). These items were included with the media (TV show or movie) format mentioned modified to align with the media format of interest in the survey that they took:

> (Eudaimonia, E1) “I like TV shows (movies) that challenge my way of seeing the world.”
>
> (Eudaimonia, E2) “I like TV shows (movies) that make me more reflective.”
>
> (Hedonism, H1) “It’s important to me that I have fun when watching a TV show (movie).”
>
> (Hedonism, H2) “TV shows (movies) that make me laugh are among my favorites.”

TV Viewing History and Demographics – TV Time App

TV Time (iOS/Android) is a mobile app through which individuals can self-report their TV and movie consumption. Data can be input both in-situ or by-recall, though the recorded app data make no explicit distinction along these lines. A user self-reporting a TV show episode as seen makes no definite statement on when the consumption occurred relative to the self-report, especially as the app allows users to batch mark entire seasons as viewed.

Though the *TV Time* app collected viewing data on both TV show and movies, the decision was made to focus exclusively on TV data, collected for each user at the episode-level, since at the time the above survey was administered, movie tracking was a new feature in the app gradually rolled out to users in the months preceding the study. The relative newness of the data presented a range of validity concerns arising from the fact unlike the TV data, which traced back to as early as 2011, depending on the user and their sign-up date, much of the movie data at the time was recorded when users first updated to the app version with movie support. This may have led to recency or related temporal biases in the movie data not present in the TV show data. Such movie-specific data concerns justified the decision to focus solely on TV show consumption data.

For each participant in the survey, raw episode-level TV consumption data were gathered from their TV Time app account. Each episode was dummy coded on 32 genres, as provided to the app by the crowdsourced television database TheTVDB.com, with an episode capable of being marked as falling under one or multiple genres and the genre labels being the same for all episodes of a given show. Demographics data – including age, gender, and country information – were gathered from data input into the *TV Time* app by the survey respondent upon account creation or, if the user chose to login with Facebook over create an e-mail address-based *TV Time* account, collected from their Facebook account.

Analysis

Descriptive Analysis

Demographics

A total of N = 1,777 responses were analyzed. This final sample for analysis was reached by first filtering 2,752 surveys collected for incomplete responses (2,181 after filtering). Then, all responses except one random response from users who completed more than one of the four surveys were dropped (2,159). Following this, users whose age, gender, and country information was not available in TV Time data were discarded (1,807). Lastly, to ensure data quality was not affected by users less familiar or engaged with the TV Time app, users who had not been registered on the app for at least 12 weeks (1,793) and active for at least 3 of those weeks as of the last day of survey data collection were filtered out (1,777).

Fully 59% (n = 1,057) of the sample were female, with a mean respondent age of 27.58 (SD = 9.49). France (n = 310), was the most common country of origin among the 91 countries represented in the data, followed by Italy (n = 288), United States (n = 244), and Brazil (n = 196). These countries alone made up 58.4% of the data set and all remaining countries failed to reach triple-digit counts in the data. As such, the country variable was collapsed into a five-level (France, Italy, US, Brazil, Other) alternative for analysis.

Predictors

Reliability of the short eudaimonia and hedonism scales was measured using Spearman-Brown formula split-half reliability–recommended by Eisinga et al. (2013) over Cronbach's alpha for two-item scales. As noted in the Methods section, the predictor questions referred to movies for some (n = 1,166) and TV shows for others (n = 611) to fit the encompassing user survey topic. The known relevance of hedonic mood and eudaimonic meaning to both TV (e.g., Adachi et al., 2018; Weaver & Laird, 1995) and movie (e.g., Oliver & Raney, 2011; Strizhakova & Krcmar, 2007) consumption gave theoretical justification to assume sufficient functional equivalence between the TV- and movie-referring eudaimonia and hedonism measures. This was supported statistically by format-level comparison of split-half reliability, showing little difference between the movie and TV cases for either eudaimonia (.8/.79) or hedonism (.68/.63) and Levene's tests showing no significant variance differences between the formats (*E1*: $F_{1,\ 1775} = 3.835$, p =.0504, Holm p = .201; *E2*: $F_{1,\ 1775} = 1.406$, p = .236, Holm p = .707; *H1*: $F_{1,\ 1775} = .945$, p = .331, Holm p = .707; *H2*: $F_{1,\ 1775} = .221$, p = .639, Holm p = .707).

Correspondingly, final predictor reliability analysis was conducted on the entire data set. Split-half reliability was .8 for eudaimonia and .67 hedonism overall, satisfactory or near satisfactory per Salkind's (2010) .7-.8 threshold. As such, the two items for each scale were averaged to generate singular eudaimonia and hedonism measures for each user. Eudaimonia tended to be higher and less varied (M = 5.58, SD = 1.21) than hedonism (M = 5.15, SD = 1.30).

Outcomes

The primary outcome variables of interest were generated by using the episode-level viewing data from the TV Time app to calculate show-level per-genre viewing history proportions representing, for a given user, the percentage of TV shows marked viewed in-app that fell into a given genre. Shows could be classified as one or more genres. Viewed show proportions were used rather than viewed episode proportions to account for potential bias resulting from differing show episode counts or genre differences in show episode counts. What is considered a valid genre can vary; given the predefined nature of the app data and to avoid potential bias introduced by selective transformation of genres, the genres examined were limited to those in the *TV Time* data, as they were originally provided. Averaging each of these per-genre proportions across all users, several of the 32 genres only marginally registered in users' viewing histories, falling near or below a .01 average and leading to a median average genre proportion value of .0398. As such, a decision was made to only retain for analyses the 16 genres whose average viewing history proportion across all users was higher than the median prominence of .0398. These 16 genres with values representing, on

Table 1. Per-genre mean (SD) viewing history proportion.

Mystery	Science Fiction	Fantasy	Adventure	Crime	Action	Comedy	Drama
0.142 (0.055)	0.152 (0.085)	0.152 (0.078)	0.171 (0.088)	0.206 (0.09)	0.217 (0.121)	0.327 (0.127)	0.615 (0.143)
Family	**Anime**	**Miniseries**	**Suspense**	**Horror**	**Romance**	**Animation**	**Thriller**
0.041 (0.037)	0.049 (0.09)	0.056 (0.038)	0.073 (0.033)	0.082 (0.05)	0.09 (0.076)	0.119 (0.146)	0.129 (0.061)

average, what proportion of the TV shows users watched fell into a particular genre are presented in Table 1.

Primary Analysis – Beta Regression Models

Beta regression models were created with each of the genre viewing history proportion variables as outcomes; eudaimonia and hedonism as the predictors of interest; and age, gender, and country of origin as control variables. Beta regression is a type of regression intended to be used with proportion and rate data (Cribari-Neto & Zeileis, 2010). As the technique cannot handle 0.0 or 1.0 outcomes, only those in between, and respondents often had genres they had never watched (i.e. 0% of viewing history), analysis was conducted with genre viewing history proportions corrected using the formula $(y * (n - 1) + 0.5)/n$ (Cribari-Neto & Zeileis, 2010; Smithson & Verkuilen, 2006) to account for these zeroes, where y represents the genre viewing history proportion value for a given user and n represents the total sample size. This correction only negligibly shifted the outcome values by an average of .00023.

The results are presented in Table 2, with each genre regression table accompanied by the pseudo R^2 as well likelihood-ratio tests comparing the full model to a simplified demographics-only model, detailed further in the following section. Beta regression variable coefficients are best understood in exponentiated form, where, for a given model, they represent the impact of a one-unit increase in the variable on the ratio of the particular genre viewing proportion to the proportion of viewed shows not in that genre (e.g., % drama/(1 – % drama)).

Both eudaimonia and hedonism present multiple significant positive and negative effects in the beta regression models. Eudaimonia had significant positive effects on mystery, mini-series, thriller, and drama viewing, and significant negative effects on family, adventure, and action viewing. Hedonism had significant positive effects on family, romance, action, and comedy viewing and significant negative effects on mystery, science-fiction, mini-series, suspense, horror, crime, thriller, and drama viewing. There were multiple models in which neither eudaimonia nor hedonism were statistically significant predictors, namely those with anime, animation, and fantasy viewing proportion as outcome variables. Family, mystery, miniseries,

Table 2. Beta regression tables results by genre.

Variable	Model	b (SE)	Z	p	Model	b (SE)	Z	p
(Intercept)	**Family**	−3.0644 (0.1351)	−22.6763	***<.000***	**Mystery**	−1.6346 (0.0752)	−21.7312	***<.000***
Eudaimonia	Pseudo R^2 =.115	−0.0316 (0.0159)	−1.9913	***0.0464***	Pseudo R^2 =.040	0.0246 (0.0091)	2.696	***0.007***
Hedonism	*LR test vs. demo-only:*	0.0992 (0.0152)	6.523	***<.000***	*LR test vs. demo-only:*	−0.0495 (0.0085)	−5.8446	***<.000***
Gender, Male (Baseline: Female)	χ^2 (2) = 45.645, ***p <.000***	−0.4833 (0.0411)	−11.7575	***<.000***	χ^2 (2) = 40.915, ***p <.000***	−0.0734 (0.0227)	−3.2307	***0.0012***
Age		−0.0184 (0.0023)	−7.9123	***<.000***		0.0014 (0.0013)	1.1328	0.2573
Country – US (Baseline: France)		0.3108 (0.0741)	4.1922	***<.000***		−0.192 (0.0426)	−4.5112	***<.000***
Country – Brazil		0.4586 (0.0728)	6.3029	***<.000***		0.0115 (0.0413)	0.2774	0.7815
Country – Italy		0.3661 (0.0656)	5.5824	***<.000***		−0.0579 (0.0369)	−1.5701	0.1164
Country – Other		0.1747 (0.0562)	3.1097	***0.0019***		−0.0657 (0.0309)	−2.1276	***0.0334***
(Intercept)	**Anime**	−2.7815 (0.1681)	−16.5514	***<.000***	**Science Fiction**	−1.8933 (0.0983)	−19.2548	***<.000***
Eudaimonia	Pseudo R^2 =.107	0.0166 (0.0198)	0.836	0.4032	Pseudo R^2 =.134	0.0037 (0.0119)	0.3117	0.7553
Hedonism	*LR test vs. demo-only:*	0.0028 (0.0187)	0.1507	0.8802	*LR test vs. demo-only:*	−0.0299 (0.0112)	−2.6725	***0.0075***
Gender, Male (Baseline: Female)	χ^2 (2) = 0.722, *p* =.697	0.3325 (0.0495)	6.7214	***<.000***	χ^2 (2) = 7.188, ***p <.027***	0.5117 (0.0293)	17.4442	***<.000***
Age		−0.0153 (0.0028)	−5.5419	***<.000***		0.006 (0.0016)	3.7661	***.0002***
Country – US (Baseline: France)		−0.1769 (0.092)	−1.9228	0.0545		−0.1658 (0.0552)	−3.005	***0.0027***
Country – Brazil		0.1231 (0.0919)	1.3386	0.1807		−0.1115 (0.0553)	−2.0172	***0.0437***
Country – Italy		0.1462 (0.0817)	1.7897	0.0735		−0.1101 (0.0494)	−2.2278	***0.0259***
Country – Other		−0.057 (0.0685)	−0.8332	0.4047		−0.1007 (0.0409)	−2.4631	***0.0138***

(*Continued*)

Table 2. (Continued).

Variable	Model	b (SE)	Z	p	Model	b (SE)	Z	p
(Intercept)	**Mini-series**	−3.2796 (0.1164)	−28.1829	***<.000***	**Fantasy**	−1.3149 (0.0953)	−13.8028	***<.000***
Eudaimonia	Pseudo R^2 =.050	0.0537 (0.0141)	3.8144	***0.0001***	Pseudo R^2 =.048	−0.0176 (0.0114)	−1.5425	0.123
Hedonism	*LR test vs. demo-only:*	−0.0555 (0.013)	−4.2669	***<.000***	*LR test vs. demo-only:*	0.0075 (0.0108)	0.6986	0.4848
Gender, Male (Baseline: Female)	χ^2 (2) = 32.771, ***p <.000***	0.1229 (0.0344)	3.5738	***.0004***	χ^2 (2) = 2.787, *p* =.248	0.094 (0.0285)	3.2996	***0.001***
Age		0.0139 (0.0018)	7.5643	***<.000***		−0.0119 (0.0017)	−7.1463	***<.000***
Country – US (Baseline: France)		−0.3319 (0.0669)	−4.9579	***<.000***		−0.1545 (0.0537)	−2.8748	***0.004***
Country – Brazil		0.0558 (0.0643)	0.8681	0.3853		0.0369 (0.052)	0.7099	0.4778
Country – Italy		0.0434 (0.0575)	0.7543	0.4507		−0.058 (0.0467)	−1.2418	0.2143
Country – Other		0.0565 (0.0483)	1.1713	0.2415		−0.0739 (0.0389)	−1.901	0.0573
(Intercept)	**Suspense**	−2.1833 (0.0835)	−26.1435	***<.000***	**Adventure**	−1.4438 (0.0909)	−15.8856	***<.000***
Eudaimonia	Pseudo R^2 =.034	0.0147 (0.0101)	1.4481	0.1476	Pseudo R^2 =.131	−0.0281 (0.0109)	−2.5754	***0.01***
Hedonism	*LR test vs. demo-only:*	−0.0422 (0.0094)	−4.4817	***<.000***	*LR test vs. demo-only:*	0.0068 (0.0104)	0.6527	0.514
Gender, Male (Baseline: Female)	χ^2 (2) = 21.734, ***p <.000***	−0.0287 (0.0253)	−1.1347	0.2565	χ^2 (2) = 6.843, ***p = .033***	0.4549 (0.0271)	16.8082	***<.000***
Age		−0.0038 (0.0014)	−2.6415	***0.0083***		−0.0056 (0.0015)	−3.6112	***.0003***
Country – US (Baseline: France)		−0.2534 (0.0475)	−5.3329	***<.000***		−0.1108 (0.0511)	−2.167	***0.0302***
Country – Brazil		−0.0411 (0.0455)	−0.9048	0.3656		−0.0227 (0.0505)	−0.4501	0.6527
Country – Italy		−0.1528 (0.0408)	−3.7467	***0.0002***		−0.0559 (0.0454)	−1.2329	0.2176
Country – Other		−0.1167 (0.0338)	−3.4564	***0.0003***		−0.0716 (0.0376)	−1.9006	0.0574

(*Continued*)

Table 2. (Continued).

Variable	Model	b (SE)	Z	p	Model	b (SE)	Z	p
(Intercept)	**Horror**	−2.0319 (0.1109)	−18.3157	***<.000***	**Crime**	−1.5124 (0.0892)	−16.9556	***<.000***
Eudaimonia	Pseudo R^2 =.016	0.0027 (0.0134)	0.2004	0.8412	Pseudo R^2 =.046	0.0013 (0.0108)	0.1243	0.9011
Hedonism	*LR test vs. demo-only:*	−0.0538 (0.0125)	−4.2936	***<.000***	*LR test vs. demo-only:*	−0.0263 (0.0102)	−2.5905	***0.0096***
Gender, Male (Baseline: Female)	χ^2 (2) = 18.648, p <.000	0.0935 (0.0334)	2.8018	***0.0051***	χ^2 (2) = 6.718, p =.035	0.0233 (0.0269)	0.8674	0.3857
Age		−0.0042 (0.0019)	−2.2296	***0.0258***		0.0123 (0.0015)	8.4233	***<.000***
Country – US (Baseline: France)		−0.0539 (0.0622)	−0.866	0.3865		−0.2465 (0.0504)	−4.888	***<.000***
Country – Brazil		0.0935 (0.0607)	1.542	0.1231		−0.1108 (0.0506)	−2.1906	***0.0285***
Country – Italy		−0.1266 (0.0554)	−2.2852	***0.0223***		−0.0732 (0.0447)	−1.6385	0.1013
Country – Other		−0.0691 (0.0459)	−1.5053	0.1322		−0.0137 (0.037)	−0.3707	0.7109
(Intercept)	**Romance**	−1.6035 (0.1113)	−14.4125	***<.000***	**Action**	−1.3113 (0.1067)	−12.2939	***<.000***
Eudaimonia	Pseudo R^2 =.269	0.0076 (0.0133)	0.5759	0.5647	Pseudo R^2 =.120	−0.0476 (0.0128)	−3.7227	***.0002***
Hedonism	*LR test vs. demo-only:*	0.0259 (0.0124)	2.0799	***0.0375***	*LR test vs. demo-only:*	0.0315 (0.0122)	2.5711	***0.0101***
Gender, Male (Baseline: Female)	χ^2 (2) = 4.617, p =.099	−0.6827 (0.0352)	−19.3981	***<.000***	χ^2 (2) = 19.423, $\boldsymbol{p}$ **<.000**	0.5223 (0.0319)	16.3891	***<.000***
Age		−0.0241 (0.002)	−11.7703	***<.000***		0 (0.0018)	−0.0165	0.9869
Country – US (Baseline: France)		−0.3567 (0.0647)	−5.514	***<.000***		−0.211 (0.06)	−3.5179	***0.0004***
Country – Brazil		0.1405 (0.0592)	2.3729	***0.0176***		−0.1081 (0.0598)	−1.8066	0.0708
Country – Italy		0.0431 (0.0523)	0.8244	0.4097		−0.0915 (0.0535)	−1.7105	0.0872
Country – Other		0.0223 (0.0441)	0.5058	0.613		−0.096 (0.0442)	−2.1721	***0.0298***

(*Continued*)

Table 2. (Continued).

Variable	Model	b (SE)	Z	p	Model	b (SE)	Z	p
(Intercept)	**Animation**	−1.9182 (0.1636)	−11.726	***<.000***	**Comedy**	−0.719 (0.0942)	−7.6294	***<.000***
Eudaimonia	Pseudo R^2 =.126	0.0351 (0.0195)	1.8014	0.0716	Pseudo R^2 =.110	−9e-04 (0.0112)	−0.084	0.9331
Hedonism	*LR test vs. demo-only:*	0.0249 (0.0184)	1.3557	0.1752	*LR test vs. demo-only:*	0.0854 (0.0107)	7.9874	***<.000***
Gender, Male (Baseline: Female)	χ^2 (2) = 5.050, p =.080	0.5124 (0.0485)	10.5718	***<.000***	χ^2 (2) = 63.029, $\boldsymbol{p}$ **<.000**	−0.1423 (0.0281)	−5.0628	***<.000***
Age		−0.0266 (0.0027)	−9.679	***<.000***		−0.0171 (0.0016)	−10.6114	***<.000***
Country – US (Baseline: France)		0.0559 (0.0906)	0.6166	0.5375		0.2495 (0.0517)	4.8283	***<.000***
Country – Brazil		0.2913 (0.0897)	3.2483	***0.0012***		0.0497 (0.0523)	0.95	0.3421
Country – Italy		0.1566 (0.0804)	1.9472	0.0515		0.1195 (0.0463)	2.5817	***0.0098***
Country – Other		0.07 (0.0674)	1.0395	0.2986		0.0531 (0.0388)	1.369	0.171
(Intercept)	**Thriller**	−2.0371 (0.0888)	−22.9483	***<.000***	**Drama**	0.6367 (0.0957)	6.6506	***<.000***
Eudaimonia	Pseudo R^2 =.098	0.0522 (0.0108)	4.8209	***<.000***	Pseudo R^2 =.107	0.0284 (0.0115)	2.4757	***0.0133***
Hedonism	*LR test vs. demo-only:*	−0.0825 (0.01)	−8.2735	***<.000***	*LR test vs. demo-only:*	−0.0799 (0.0109)	−7.3267	***<.000***
Gender, Male (Baseline: Female)	χ^2 (2) = 87.257, $\boldsymbol{p}$ **<.000**	0.1504 (0.0265)	5.6786	***<.000***	χ^2 (2) = 58.145, $\boldsymbol{p}$ **<.000**	−0.2178 (0.0286)	−7.6233	***<.000***
Age		0.0097 (0.0014)	6.6986	***<.000***		0.0114 (0.0016)	7.0775	***<.000***
Country – US (Baseline: France)		−0.4007 (0.0517)	−7.7576	***<.000***		−0.4556 (0.0528)	−8.622	***<.000***
Country – Brazil		−0.1165 (0.0498)	−2.3382	***0.0194***		−0.1585 (0.0535)	−2.9619	***0.0031***
Country – Italy		−0.0569 (0.0437)	−1.3024	0.1928		−0.0742 (0.0479)	−1.548	0.1216
Country – Other		−0.0178 (0.0365)	−0.4895	0.6245		−0.1119 (0.0399)	−2.8045	***0.005***

action, thriller, and drama viewing were significantly impacted by both eudaimonia and hedonism, with these effects consistently oppositely valenced. Even with the same model specification, variance explained varied depending on the genre. Pseudo R^2 values ranged from a low of .016 for the horror model to a high of .269 for the romance model.

Comparisons to Demographics-Only Models

In order to examine whether the inclusion of the eudaimonia and hedonism measures in addition to commonly examined demographic variables provided improvements in fit, likelihood-ratio tests were conducted. Each genre full model, containing demographic variables as well as eudaimonia and hedonism as predictors, was compared against a demographics-only model for the genre. The results of each of these tests are presented in Table 2 in the respective model genre label cell, under *LR-test vs. demo-only*. These tests suggested that in the majority of cases, models including the eudaimonia and hedonism measures were a significantly improved fit to the data than the demographics-only models. The only exceptions occurred in the case of anime, fantasy, romance, and animation.

Discussion

Hedonism and eudaimonia effects on genre prominence in respondents' TV show viewing history were present consistently across a broad and intuitively face valid range of genres, even when controlling for gender, age, and country of origin. Likelihood-ratio tests also suggested these models generally fit the data significantly better than demographics-only models. Higher eudaimonia respondents tended to have a higher proportion of mystery, mini-series, thriller, and drama shows and a lower proportion of family, adventure, and action shows in their viewing history. Respondents who indicated higher hedonic motivations for entertainment consumption tended to have higher proportions of family, romance, action, and comedy and lower proportions of mystery, sci-fi, mini-series, suspense, horror, crime, thriller, and drama in their viewing history.

Even though the present study examines TV rather than movie genre preference and includes a different set of genres, the results display broad parallels to the Oliver and Raney (2011) as well as the Igartua and Barrios (2013) studies, with regard to both eudaimonia and hedonism effects. Positive hedonism effects on action and comedy preference observed presently match those found in those two studies, with the positive effect on romance preference in the Igartua and Barrios study also matched. Positive eudaimonia effects on drama and thriller preference match the effects observed by Igartua and Barrios, while the negative eudaimonia effect on action matches findings in both the Igartua and Barrios study and the Oliver and Raney study. Negative hedonism effects observed find few matches here, relative to their number, with only the thriller, suspense, and drama effects projecting onto the Igartua and Barrios findings.

As previously discussed, the results present a modestly more rigorous expansion of Oliver and Raney (2011) and Igartua and Barrios (2013) studies. Despite the fact that both typical surveys and mobile app data like that examined in the present study ultimately boil down to different variations on the self-report approach at the core prone to many similar biases, the app data provide two modest but distinct methodological advantages. The first is that a survey as commonly utilized in studies like the above and countless more is constrained to by-recall measurement only, while the "always-open" nature of the app-based approach provides *additional* potential, perhaps not fully exercised by the app user, to get some degree of in-situ measurement in a way a single administration of a survey cannot, while remaining similarly capable of collecting by-recall data. The second is that, even accounting for equivalent self-report related validity concerns, the data collected by the app in the present study (and any similar apps that enable individuals to track consumption of certain content) inherently more directly measures whether or not they consumed certain pieces of content, rather than relying on an abstract "not at all" to "very much" Likert-type measure of genre liking (as was the case with both the Oliver and Raney (2011) and Igartua and Barrios (2013) studies). In any preference measurement context where the end goal is to glean greater insight into past or potential future consumption, a more direct measurement of consumption would be preferable over a measurement of liking holding constant self-report biases in both cases.

Using these more direct self-report measures of media consumption collected in a mobile app, the findings show that, even controlling for demographic variables – including a respondent country-of-origin variable not considered by Oliver and Raney or Igartua and Barrios – eudaimonia and hedonism have statistically significant effects on the prevalence of various genres in individuals' TV show viewing history. Further research on these effects is needed, ideally using the full question batteries for the predictors and more direct passive outcome measures (e.g., De Vreese & Neijens, 2016). Development of some type of indirectly inferred eudaimonia and hedonism measure, perhaps based on consumption measures of certain genres, may also prove beneficial.

That the effects in the present study were observed in data collected via a media consumption self-monitoring app also presents significant methodological implications worth consideration in future research. The results highlight the viability of such apps as data collection tools in media preference studies, providing a type of ecologically valid, big-picture perspective into the media consumption tendencies of participants. The TV Time app provides a mostly unprompted, organic, over-time media consumption data collection context. This app may thus provide slightly more ecologically and externally valid data than do the regularly scheduled prompts of ecological momentary assessment (EMA) style approaches by not constraining when responses can be provided to set intervals, as is common with EMA-type methods (e.g., Heron et al., 2017). The mobile app method comes with its own set of limitations and validity concerns, as discussed further in a subsequent section, but shows promise as a potential data collection approach. Additional research on the viability of such data collection tools in the media preference research context is needed.

The findings point to a broader importance of psychometrics in media consumer research. Though demographics may in many cases implicitly be presumed to explain audience genre preferences, the present study shows that the addition of eudaimonia and hedonism measures consistently improve the fit of the model to the data in statistically significant ways. Psychometric measures like these should be evaluated for their potential contribution to explained variance when conducting consumer research in the media industry. Such measures and related theories implicitly carry potential utility as features and frameworks that can provide predictive value and whose explanatory logic can be projected onto or combined with various data science techniques.

The fact that known psychometric effects on individuals' media preferences can be observed within self-report data collected via mobile app is of broadly significant importance in the context of consumer research. It highlights the utility of media consumption data self-reported via mobile apps, underscoring its viability as a consumption metric in which real individual differences measurably manifest depending on various factors. As appropriate depending on research scope and measurement needs, such data should receive further attention as a potential viable and valid self-reported media consumption measure.

Limitations

Any self-report media consumption measure carries with it typical concerns related to self-report measures. Though the nature of over time, mobile-app-based self-reporting of TV consumption carries with it certain distinct advantages over typical single time-point survey measures, such as lack of hypothesis guessing or order effect concerns, some concerns remain. Recency biases (e.g., Garbinsky et al., 2014), liking and memory effects (e.g., Youn et al., 2001), and user desirability bias (e.g., Krumpal, 2013), among others, may still influence what users self-report as viewed in the app. For more recently consumed TV shows, higher salience in individuals' minds is understandable, as is the tendency to remember shows one likes and shows related to topics made salient by other media. And given the identity construction functions that media consumption can serve (e.g., Ots & Hartmann, 2015), in essence serving as an association of oneself with the brand of a media product, desirability bias in what an individual reports having viewed is unsurprising.

The usage of an abbreviated version of Oliver and Raney (2011) eudaimonia and hedonism measures was necessary given the context of the measures' placement at the end of a lengthy consumer research survey and the secondary, unrelated nature of the measures in relation to the goals of said survey. Although the two highest factor loading items were chosen from each of the scales, a study using the full eudaimonia and hedonism measures may provide more nuanced results. However, that the abbreviated measures still presented significant effects is promising for these measures in terms of the viability of their use in limited screen space, limited attention scenarios like mobile apps.

The demographic variables available for analysis via the TV Time app data were highly limited in scope. Beyond age, gender, and country of origin, controlling for other demographic variables such as political ideology, education, or income may provide different results, and these variables may themselves present notable main effects when controlling for eudaimonia and hedonism. A more comprehensive set of demographic variables should be collected and controlled for in future research in this direction.

Conclusion

Eudaimonia and hedonism present significant effects on TV show genre preference, and these effects are visible in entertainment self-monitoring apps where users can self-report the content they have seen. Higher eudaimonia individuals tend to have a higher proportion of mystery, mini-series, thriller, and drama shows and a lower proportion of family, adventure, and action shows in their viewing history. Higher hedonism is associated with a higher proportion of family, romance, action, and comedy and lower proportions of mystery, sci-fi, mini-series, suspense, horror, crime, thriller, and drama in their viewing history. Models including these two measures fit the data significantly better than those that only include demographics variables. Further consideration of eudaimonia, hedonism, and other psychometric measures in addition to traditionally examined demographic considerations may prove beneficial in consumer media preference contexts, and additional research is necessary on the potential utility of media consumption data self-reported via mobile app in media preference research.

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