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The dimensions of polychronicity as drivers of multiple media use:

A Multiple Media User Typology (MMU-T).

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Abstract

This article examines selected drivers of multiple media use, to investigate why individuals' choose to multitask with media. A survey of 315 Digital Natives reveals that multiple media use is predicted by the dimensions of polychronicity (preference to multitask with media). The discovery of heterogeneity in the impact of the dimensions of polychronicity on multiple media use indicates that this functional relationship varies between individuals, revealing a unique typology. The Multiple Media User Typology (MMU-T) comprises 'Information seekers', 'Connected' and 'Instinctives'. Distinct patterns of multiple media use are identified for each segment, with associated implications for multi-media advertising campaign planning.

Management slant

- A typology of multiple media users is discovered; the Multiple Media User Typology (or MMU-T) comprises three segments: 'Information seekers', 'Connected' and 'Instinctives'.

- Distinct patterns of multiple media use are identified for each segment ('Information seekers', 'Connected' and 'Instinctives') of the MMU-T.

- The power of the MMU-T comes to the fore at a key stage in the multi-media planning process; once top level media channel decisions are confirmed.

- The significant determinants of multiple media use for each segment of the MMU-T provide important new insights to multi-media planners.

1.0 Introduction

Whether at home, work, or on the move, contemporary media alternatives allow individuals to exert a high level of control over their media consumption; for example, through the use of on-demand media services or time-shift viewing possibilities (Enoch and Johnson, 2010; Pilotta and Schultz, 2005; Webster and Ksiazek, 2012). Within the media environment, a characteristic of individuals' consumption behavior is multiple media use, which represents a distinct case of multitasking (Rosen, Carrier and Cheever, 2013). Multitasking is defined as the completion of multiple tasks in the same time period, by engaging in frequent switches between individual tasks (Delbridge, 2000). Consistently, multiple media use involves switching between selected media alternatives; such as surfing the internet while texting, or watching television and attending to incoming social media alerts (Foehr, 2006; Pilotta, Shultz, Drenik and Rist, 2004; Pilotta and Shultz, 2005). Fast and frequent switching between media is detected (Yeykelis, Cummings and Reeves, 2014); for example, research indicates an average of four switches per minute between TV and computer (Brasel and Gips, 2011) and a resulting variation in individuals' attention levels (Brasel and Gips, 2011; Pilotta and Schultz, 2005). The context specificity of multiple media use (for example, relaxing at home as compared with travelling to and from work) guides individuals to create their own personal 'media multitasking portfolios' (Robinson, 2017a). Taking into consideration the array of available media channels, countless combinations of media are possible (Carrier, Rosen, Cheever, and Lim*,* 2015). The multiple media use of individuals and their preference for combining assorted media are the focal interest of the paper.

Extant literature indicates that the topic of multiple media use represents an emergent research domain (Lin, 2009). Several prominent combinations of multiple media use are identified, for example: TV and internet; email and texting; phone and TV (Carrier *et al.,* 2015; Foehr, 2006; Pilotta *et al.,* 2004; Pilotta and Shultz, 2005; Segijn *et al*. 2017). Research associates media ownership and audience demographics with multiple media use (Carrier *et al*, 2009; Carrier *et al.,* 2015; Jeong and Fishbein, 2007; Wang and Tchernev, 2012; Duff, Yoon, Wang and Anghelcev, 2014; Srivastava *et al*., 2016) and examines traits as predictors of media multitasking (Duff *et al*., 2014; Jeong and Fishbein, 2007; Rubenking, 2016; Yang and Zhu, 2016). Although these studies provide insights into individuals' characteristics, the literature remains incomplete on the fundamental question of why individuals engage in multiple media use. Consumer behavior theory helps to answer this question through evidence that preference precedes behavior (Lavidge and Steiner, 1961; Lee, Amir and Ariely, 2009). Further guidance is provided by the organizational literature. With its long tradition in the study of multitasking, previous research reveals that polychronicity represents the preference to multitask (Konig and Waller, 2010). Moreover, there is some empirical evidence in the organizational setting for the impact of polychronicity on multitasking (Conte and Gintoft, 2005; Magen 2017).

In the specific context of multiple media use, three studies are identified which confirm the functional relationship between polychronicity and multiple media use (Kononova and Chiang, 2015; Srivastava, Nakazawa and Chen, 2016; Rubenking, 2016). However, these studies suffer from the following drawbacks: (a) they employ general, rather than (multiple media use) context specific conceptualizations of polychronicity; (b) despite evidence to the contrary (for example, Palmer and Schoorman, 1999), model polychronicity as a unidimensional construct, and (c) treat multiple media use as a single behavior, rather than one that can take many forms and is contextually defined. In addressing these deficiencies, this study contributes to subject knowledge through the examination of preference, offering new insights for media practitioners endeavoring to reach multiple media users effectively and efficiently.

2.0 Determinants of Multiple media use

An evaluation of extant empirical studies examining the precursors to multiple media use is summarized in Table 1. In this emerging research domain, the literature reveals a limited body of work attempting to establish the determinants of multiple media use. Appraisal of these studies reveals five main themes: media ownership and access; demographics; personal traits; individual motivations and the preference to multitask, also known as polychronicity. Each theme is considered in turn.

Table 1: Determinants of multiple media use

Empirical study	**Determinants**	**Media**	**Sample**
Jeong and Fishbein (2007)	Media ownership and access; sensation seeking	Multiple media	14-16 year olds U.S.
Carrier *et al*. (2009)	Age; generations	Multiple media	Adults 18-44 U.S.
Ophir, Nass and Wagner (2009)	Media usage; gender	Multiple media	University students U.S.
Bardhi, Rohm and Sultan (2010)	Need for control; efficiency; engagement; assimilation	Multiple media	Students aged 20-23 U.S.
Wang and Tchernev (2012)	Media access; personal needs; habit; gratifications sought	Multiple media	Students U.S.
Kononova (2013)	Media ownership; gender; sensation seeking	Multiple media	University students Kuwait; Russia; U.S.
Duff *et al.* (2014)	Age; gender; personal control; need for simplicity; sensation seeking; creativity	Multiple media	Student/national sample U.S.
Hwang, Kim and Jeong (2014)	Education; Habit; enjoyment; information	Multiple media	Adults 19-59 Korea
Kononova and Chiang (2015)	Media ownership; polychronicity; control; entertainment; connection; addiction	Multiple media	Adults U.S. and Taiwan
Rubenking (2016)	Age; gender; media access; multitasking preference; immersive tendency	Media with TV only	Undergraduate students 18-39 U.S.
Srivastava *et al.* (2016)	Age; education; media ownership; preference for multitasking	Multiple media	Undergraduate students U.S.
Yang and Zhu (2016)	Age; media usage time; sensation seeking; impulsivity	Multiple media	Adolescents 11-18 China
Segijn *et al.* (2017)	Age; gender; education; screen ownership	Multiple screens	National sample Netherlands

Predictably, media ownership and access are confirmed prerequisites of multiple media use. Evidence is found of a significant positive association between ownership of televisions, radios, laptops, tablets or smartphones and multiple media use (Jeong and Fishbein, 2007; Kononova and Chiang, 2015; Wang and Tchernev, 2012; Srivastava *et al.*, 2016; Segijn *et al.,* 2017). Extant studies also indicate that ease of media access is an important requirement for multiple media use (Jeong and Fishbein, 2007; Wang and Tchernev, 2012; Rubenking, 2016). For example, when an individual is watching the television, the presence of a smartphone or tablet within close proximity is found to increase the likelihood of multiple media use (Rubenking, 2016). These findings are unsurprising, since the physical presence of media devices is an obvious prerequisite for such behavior.

Selected demographic factors, including age, gender and education are also associated with multiple media use. A number of studies confirm that Digital Natives (classified by Prensky (2001, p.1) as 'all native speakers of the digital language of computers, video games and the Internet') are significantly more likely to use multiple media than Digital Immigrants (born before 1980) (Carrier *et al*., 2009; Carrier *et al.,* 2015; Jeong and Fishbein, 2007; Wang and Tchernev, 2012; Duff *et al*., 2014; Srivastava *et al*., 2016; Segijn *et al.* 2017). Despite the popular view that females are the more prolific multitaskers, the evidence with respect to gender as a determinant of multiple media use is mixed. Some studies have revealed females rather than males as the prominent multitaskers (Jeong and Fishbein, 2007; Duff *et al*., 2014; Segijn *et al.* 2017), but others have not identified gender differences (for example, Ophir, Nass and Wagner, 2009; Kononova, 2013). Education level is also examined to a limited extent; a higher education level is linked with multiple media use in studies by Hwang *et al.* (2014) and Segijn *et al.* (2017), whereas Voorveld *et al.* (2014) identified those with lower education levels as less likely to multitask with media. Although these investigations provide helpful background information regarding audience characteristics, the studies are largely descriptive and do not provide insight into why individuals choose to multitask with media.

Nevertheless, the literature also uncovers an explanatory theme, comprising evidence of the significant impact of selected personal traits on multiple media use. Several studies identify a predisposition towards sensation seeking (which alludes to 'new and exciting experiences' and 'exploring strange places', Hoyle *et al.,* 2002) as a significant positive determinant of multiple media use (Duff *et al*., 2014; Jeong and Fishbein, 2007; Kononova, 2013; Yang and Zhu, 2016). Empirical studies also examine further personal traits; significant positive associations are found between: creativity (Duff *et al*., 2014), impulsivity (Yang and Zhu, 2016), immersive tendency (Rubenking, 2016) and multiple media use. It is worth noting however, that claims of the direct impact of personal traits on behavior are controversial (Llewellyn and Wilson, 2003), with some arguing that personality traits have only indirect influence on behavior (for example, Ajzen and Fishbein, 1980).

Individuals' motivations form another theme in the literature, revealing a variety of reasons for multiple media use. Empirical work reveals that enhanced media engagement is considered to be achieved with a combination of media, as opposed to a single medium (Bardhi *et al*., 2010). Agreement also exists regarding the habitual nature of multiple media use (Hwang *et al*., 2014; Wang and Tchernev, 2012), even to the extent that some feel driven (by an addiction) to multitask with media (Kononova and Chiang, 2015). Alongside the desire for personal efficiency (Bardhi *et al*., 2010) and simplicity when using multiple media (Duff *et al.,* 2014), the need for control over the array of available media alternatives is highlighted in three separate studies (Bardhi *et al*., 2010; Duff *et al*., 2014; Kononova and Chiang, 2015). In a similar vein, a wish to gather information from a range of sources (Hwang, Kim and Jeong, 2014) and the ability to assimilate multiple streams of information (Bardhi *et al.,* 2010) are also confirmed precursors for multiple media use. Social and emotional motivations also feature, with the need for connection with others identified as a social motive for multiple media use (Kononova and Chiang, 2015). Emotional determinants are also examined, revealing significant positive relationships between: gratification (Wang and Tchernev, 2012), enjoyment (Hwang *et al.,* 2014); entertainment (Kononova and Chiang, 2015) and multiple media use. While the above studies represent notable contributions and advance subject knowledge beyond simple description; the majority omit to account for, or examine, the underlying preference for multiple media use. This omission is surprising, given the considerable debate and empirical evidence in the marketing literature, of a significant relationship between preference and behavior (Lavidge and Steiner, 1961; Lee, Amir and Ariely, 2009).

Consistent with this assertion, the most instructive theme in this emergent literature is the preference to multitask, known as polychronicity. Defined as 'the preference for doing several things at a time' (Konig and Waller, 2010, p.175), polychronicity is identified as a preference concept relevant to multiple media use. In the media context, polychronicity represents individuals' preference for using two, three or more media in combination. A protracted history of studies examining the concept of polychroncicty is uncovered in the organizational literature (for example, Bluedorn *et al*., 1999; Palmer and Schoorman, 1999); empirical studies in an organizational setting dominate research on the impact of polychronicity on multitasking behavior (for example, Conte and Gintoft, 2005; Grawitch and Barber, 2013; Magen, 2017). In the media context, three studies investigating the relationship between preference for multitasking (Rubenking, 2016; Srivastava *et al*., 2016) or polychronicity (Kononova and Chiang, 2015) and multiple media use are discovered. 'Multitasking preference' is found to predict greater time spent media multitasking by Rubenking (2016). In support of this finding, a significant positive relationship between the 'preference for multitasking' and the frequency of online, offline and mixed media multitasking behaviors is determined by Srivastava *et al.* (2016). Polychronicity is examined by Kononova and Chiang (2015), who also establish that polychronicity positively predicts the extent of media multitasking. Hence, in all three studies, polychronicity is a confirmed determinant of multiple media use.

However, a more detailed scrutiny of this empirical work exposes a number of concerns. An appraisal of the measures of preference or polychronicity used in the above-mentioned studies reveals that the Multitasking Preference Inventory (MPI), a general measure of multitasking for use in the organizational context (Poposki and Oswald, 2010) is used by Rubenking (2016). Alternatively, a basic four item general measure of the preference to multitask, 'based on items used by Xu (2008)' is used by Srivastava *et al.,* (2016, p.724). To measure polychronicity, Kononova and Chaing (2015) employ the Polychronic - Monochronic Tendency Scale (PMTS), specifically developed as a general scale (Lindquist and Kaufman, 2007). Hence, it is evident that all three studies employ general (rather than media specific) measures of preference or polychronicity. However, consultation of the consumer behavior literature advises against general measures of specific intention in the Theory of Planned Behavior (Ajzen, 1991). Accordingly, a media context specific scale, rather than a general measure is advised to measure polychronicity in the context of multiple media use. Additionally, a detailed inspection of the above measures indicates that without exception, they are unidimensional. However, it is contended that this approach may lead to a potential reduction in detail and depth of understanding of individuals' preference for multiple media use. In addition, the adoption of a unidimensional approach is contrary to the aforementioned organizational literature, which reveals agreement about the multidimensional nature of polychronicity (for example, Palmer and Schoorman, 1999). Consistently, in the media context, it is reasoned that treating polychronicity as a unidimensional (or higher order) construct precludes the comprehensive examination of individuals' preference for media use. Additionally, this treatment does not align with the multifaceted nature of multiple media use (ascertained in Robinson, 2017b; Robinson and Kalafatis, 2017). Further inspection also reveals that in two of the studies multiple media use is treated as a single behavior, rather than one which can take several forms in various settings (Rubenking, 2016;

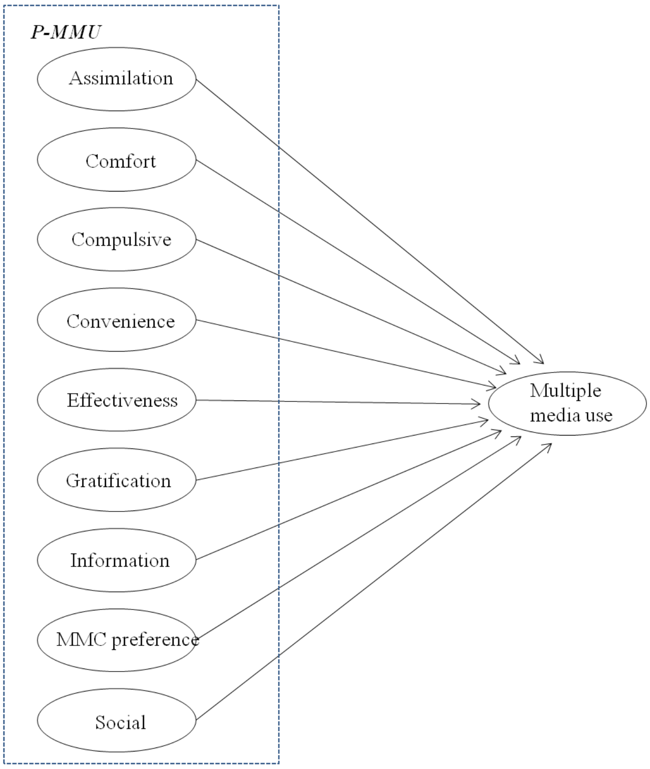
Srivastava *et al*., 2016). Yet single behavior treatment precludes the granular examination of different combinations of multiple media use. Hence, such treatment is deemed an oversimplification of this complex behavioral phenomenon, which includes numerous media combinations (Carrier *et al.,* 2015; Foehr, 2006; Pilotta *et al.,* 2004; Pilotta and Shultz, 2005; Segijn *et al*. 2017) in various settings (Enoch and Johnson, 2010).

3.0 Conceptual framework and research objectives

Overcoming the explanatory restrictions of descriptive research, opacity relating to the indirect impact of traits and nomological ambiguity of motivational variables, the concept of polychronicity (a manifestation of preference) is identified as a potential driver in the study of individuals' multiple media use. Reviewing the studies that examine the functional relationship between polychronicity and multiple media use leads to: (a) questions resulting from the use of general (non-multiple media use specific) measures of polychronicity, (b) concerns relating to the possible confounding effects resulting from unidimensional treatment of polychronicity and (c) lack of clarity due to treating multiple media use as a single behavior. The conceptual framework in Figure 1 address the first two of the above concerns; while adopting the MMI measure to operationalize multiple media use (see section 4.1) is a response to the last concern.

The departure point, adhering to recommendations by Ajzen (1991), is the employment of a multiple media specific measure of polychronicity. Consistent with Palmer and Schoorman (1999), the exploratory research by Robinson (2017b) uncovered a multi-dimensional structure and identified the following nine dimensions of polychronicity specifically related to multiple media use. 'Comfort with multiple media use' incorporates feelings of ease and confidence with multitasking, while the strength of compulsion to multitask with media is also recognized in the 'compulsive addictive' dimension. 'Multi-media channel preference' emphasizes the predilection for switching between media, while 'convenience' characterizes competency in switching between media. 'Emotional gratification' denotes affective states such as enjoyment and relaxation in the preference for multiple media use, whereas a sense of belonging and feelings of connection and closeness to others are emphasized in 'social benefits'. Aspects of personal productivity are evident in 'effectiveness and efficiency' which relates to efficacy in terms of time and effort. 'Information and knowledge' signifies the desire for multiple informational perspectives and 'assimilation' symbolizes an aspiration to make sense of information complexity and overload. The above dimensions were developed into the Polychronicity - Multiple Media Use (P-MMU) scale by Robinson and Kalafatis (2017).

Figure 1: Conceptual framework



The general hypothesis is that there is a positive relationship between each of the dimensions of the P-MMU scale and multiple media use. However, due to numerous possible multiple media combinations (Carrier *et al*., 2015; Foehr, 2006; Pilotta *et al.,* 2004; Pilotta and Shultz, 2005; Segijn *et al*., 2017), the expectation is of differential behavior in the nature and strength of these relationships. In other words, it is reasonable to expect that different preference dimensions of polychronicity will apply more or less in different multiple media situations. For example, for an individual relaxing at home in the evening (watching TV, attending to social media alerts on their smartphone and browsing online on a tablet), 'comfort with multiple media use' and 'convenience' preference dimensions may drive multiple media use. However, the preferences of someone travelling by train to work in the morning, checking text messages and social media channels on their smartphone to obtain the latest news, are likely to include: 'information and knowledge', 'multi-media channel preference' and 'effectiveness and efficiency' dimensions. Examining the differential impact of the dimensions of polychronicity on multiple media use will yield insights into preference-to-behavior patterns. Moreover, a deeper understanding of the impact of underlying preference structures on behavior will result in more efficient media targeting.

This leads to the initial objective:

- An investigation of the homogeneity of the impact of the dimensions of the P-MMU on multiple media use.

If the above expected heterogeneity, idiosyncratic of asymmetry in functional relationships is supported, the next objective is:

- Using the structure of the functional relationships between the dimensions of the P-MMU and multiple media use, group individuals into segments.

Finally, existence of groups or segments necessitates the examination of their underlying structures and associations. Thus the final objectives are:

- Identification of specific segment-by-segment preferences for multiple media use.

- Characterization of segments as a function of the identified combinations of multiple media use.

4.0 Method

4.1. Measures

As stated above, the P-MMU scale is used to operationalize polychronicity (Robinson and Kalafatis, 2017). Each of the nine dimensions of the P-MMU is reflective and metrics are obtained using four (except compulsive addictive which has three) seven-point item Likert scales anchored on ‘strongly agree’ and ‘strongly disagree’ (Appendix 1). For multitasking (i.e., multiple media use), information is collected about use and cross-use of the following media using the MMI measure (Ophir *et al.,* 2009): surfing the internet, reading magazines, reading newspapers, text messaging, watching TV, listening to radio, going to the cinema, and using social media. Specifically, (a) average number of hours per week spent on each of the media (number of hours), and (b) use of one media while at the same time engaging with each of the other media (four item scale anchored on ‘most of the time’ and ‘never’). The adopted operationalization results in a weighted index of different media use. Demographic measures include age and gender. In addition, information is collected about innovativeness with technology (Agarwal and Prasad, 1998) and sensation seeking (Hoyle *et al*., 2002), as possible psychographic bases for profiling resulting segments. Each is operationalized as a four item scale, using a seven-point Likert scale.

4.2. Sample and data collection procedure

Employing a cross sectional design, data are collected using a web-based self-completion survey from a sample of U.K. Digital Natives (adults born after 1980; Prensky, 2001) provided by a specialist list broker. During survey administration, the nine dimensions and items within each dimension are randomized. 315 usable replies are obtained from a balanced sample of male and female respondents (50% each) and age groups (15-19, 30%; 20-24, 35% and 25-36, 35%).

5.0 Analysis

The multi-step analytical framework in Table 2 is broadly similar to Mourad and Valette-Florence (2016). The first two steps involve the application of fsQCA (fuzzy-set qualitative comparative analysis). fsQCA is a response to calls by Woodside (2013) to question the symmetry of functional relationships between variables. The technique ‘uses combinatorial logic, fuzzy set theory and Boolean minimization to work out what combination of case characteristics may be necessary or sufficient to produce an outcome' (Kent, 2008). fsQCA is an exploratory approach designed to identify alternative causal configurations that link to an outcome. In step one, analysis seeks to establish existence of multiple joint configurations of the P-MMU dimensions as predictors of multiple media use. Confirmation of complex causal patterns will imply structural heterogeneity in functional relationships. Before proceeding, in step two, the predictive validity of the fsQCA results is assessed.

The next five analytical steps utilize SmartPLS (v 3.2.6; Ringle, Wende, and Becker, 2015), use bootstrapping (5000 re-samples) to determine statistical significance and adhere to the analytical approach in Hair *et al.* (2016a and 2018), Matthews *et al.* (2016) and Sarstedt, Ringle and Hair (2017). Testing, and if needed, carrying out appropriate purification, the psychometric properties of the multi-item scales is the purpose of analysis in step three, before moving on to test the research model in step four. Although examination of the overall model is not the focal interest of this study; the analysis, (a) provides a departure point regarding the significance of the functional relationships between the P-MMU dimensions and multiple media use and goodness of fit indexes, and (b) test the model's predictive validity. In step five, finite mixture PLS (FIMIX-PLS) provides information about the appropriate number of segments. FIMIX-PLS is a latent class approach, designed to uncover unobserved heterogeneity that 'occurs when there are significant differences in model relationships between groups of data' (Hair *et al.*, 2016, p. 64).

Although FIMIX-PLS offers important insights into unobserved heterogeneity in functional relationships, Sarstedt, Ringle and Hair (2017) state that 'FIMIX-PLS is clearly limited in terms of correctly identifying the underlying segment structure that the group-specific path coefficients define ' (p. 206). Hair *et al*. (2018) explain that 'FIMIX-PLS is only capable of capturing heterogeneity in the structural model relationships and cannot account for heterogeneity in the measurements model, which limits its usefulness for empirical research settings.' (p. 178). Sarstedt, Ringle and Hair (2017) report on a number of alternative approaches and conclude that 'In light of their advantages, a combination of FIMIX-PLS with PLS-POS, PLS-GAS or PLS-IRRS is particularly useful' (p. 208). Becker *et al.* (2013) demonstrate that PLS-POS (prediction orientated segmentation) performs well in cases of segmentation and Hair *et al.* (2018, p. 178) explain that 'PLS-POS computes each observation's distance to its own segment as well as other segments to decide on its group membership. When an observation has the shortest distance to its own segment, it remains in the current segment. Otherwise, the method (re-)assigns the observations to the alternative segment for which it exhibits the shortest distance.' Applying PLS-POS, a refined segmentation membership structure is obtained and used to examine inter-segment differences in the behavior of the research model's functional relationships. Using the importance-performance map analysis (IPMA) procedure in SmartPLS analysis in step 7 generates insight into the relative importance of the P-MMU dimensions as determinants of multiple media use. According to Ringle and Sarstedt (2016, p. 1866), the goal of IPMA 'is to identify predecessors that have a relatively high importance for the target construct (i.e. those that have a strong total effect), but also have a relatively low performance (i.e. low average latent variable scores).'

Analysis, in the form of chi-square tests of association and ANOVA comparisons of mean values, designed to profile the segments is carried out in step 8. Throughout the analysis, the MMI formula by Ophir *et al*. (2009) is used to calculate multiple media use. MMI is a trait media multitasking index calculated as a weighted average of different media use and consequently indicates the average amount of multiple media use during a typical hour of media usage. Following the examination of cross-media behavior, only: surfing the internet, texting, watching TV and use of social media are used in the analysis (on the basis of mean cross-media usage between these media exceeding the scale mid-point).

Table 2: Analytical framework

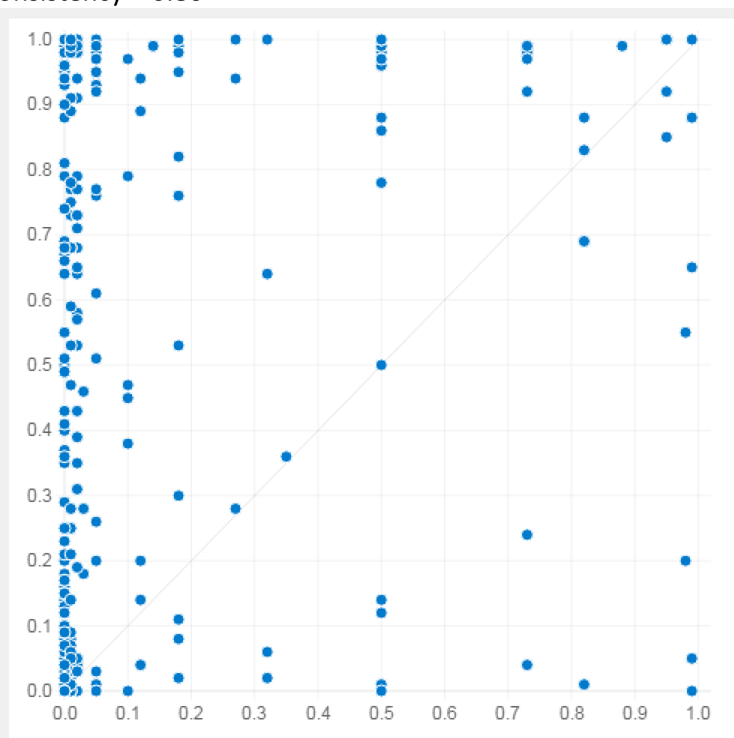
Analytical technique		
fsQCA	Step 1 - Testing the assumption of symmetric functional relationships in the research model	Identify and examine alternative causal configurations
	Step 2 - Confirmation of predictive validity	Randomly split the sample into modeling and hold-out and compare solutions
PLS	Step 3 - Testing the measurement model	Examine the psychometric (reliability and validity) properties of the multi-item scales
	Step 4 - Testing the structural model	Testing significance of the functional relationships, evaluating goodness of fit indexes and confirming predictive validity
	Step 5 – Determine number of segments	FIMIX-PLS likelihood based information criteria for different segment numbers help determine number of segments
	Step 6 – Refine segmentation membership and obtain solutions for each segment	The refined segment membership from PLS-POS is used to examine inter-segment heterogeneity
	Step 7 – Examination of the relative importance of the P-MMU dimensions	The IPMA procedure provides information about the total effects of the P-MMU dimensions on multiple media use
Chi square and ANOVA tests	Step 8 – Profiling the segments	Testing for associations between the segments and demographic characteristics and examining mean score differences between the segments

5.1. fsQCA

Using fsQCA 3.0 software developed by Ragin (2017), the variables are transformed into fuzzy sets following a procedure similar to Ali, Kan and Sarstedt (2016). Mean scores for each variable are calculated as the average of their respective scale items. The direct calibration method is implemented, applying the 75th, 50th and 25th percentiles as anchors to corresponding full membership, cross-over point and full non-membership. Figure 2 is a plot between multiple media use (dependent variable - Y axis) and the P-MMU dimensions (independent variables - X axis). Consistency is analogous to correlation and according to Woodside (2012, p. 253) 'indicates whether or not the model is dependable in accuracy … The recommendation here is that the consistency index should be greater than .85'. Coverage is analogous to coefficient of determination and 'estimates the relevancy of a model in estimating high membership scores in the outcome condition. The coverage index should typically range between .05 and higher' (Woodside, 2015, p. 253). The corresponding indices in Figure 2 exceed the recommended benchmarks and the pattern indicates an asymmetric relationship between values of the P-MMU dimensions and multiple media use. Low values of combinations of the P-MMU dimensions associate with both low and high values of multiple media use. In other words multiple media use is not consistently related to values of the nine P-MMU dimensions.

Figure 2: XY-plot for multiple media use = f (assimilation, comfort, compulsive, convenience, effectiveness, gratification, information, MMC preference, social)

Consistency = 0.80



Coverage = 0.28

The results from fsQCA analysis are presented in Table 3, and the notation follows suggestions by Fiss (2011) and Rangin and Fiss (2008). Table 3 shows the existence of 10 causal pathway configurations leading to multiple media use. The consistency and raw coverage indices for each combination, as well as for the overall solution, exceed recommended benchmarks. Identification of a large number of causal pathways indicates considerable complexity or diversity in the effects of the MMU dimensions as determinants of multiple media use. None of the MMU dimensions is a core condition (presence or absence) in more than two configurations and examination of their patterns indicates notable structural divergence. For example, although configurations 1 and 2 demonstrate similar patterns in six dimensions (compulsive, convenience, effectiveness, gratification, information and social) and clear separation in one dimension (MMC preference), differences in assimilation and comfort make interpretation difficult.

Table 3: fsQCA configurations for multiple media use

	Solutions									
Configurations	1	2	3	4	5	6	7	8	9	10
Assimilation	●		•	Ø	●	ø	ø	Ø	•	
Comfort		•	Ø	ø	Ø	ø	•	•	•	ø
Compulsive	•	•	ø	•	•	ø	●	●	•	•
Convenience	•	•	●	ø	ø	●	•	•	•	•
Effectiveness	•	•	ø	ø	ø	•	•	•	ø	•
Gratification	•	•	ø	ø	●	ø	●	ø	•	•
Information	•	•	ø	●	ø	•	ø	●	ø	•
MMC preference	ø	●	ø	ø	ø	•	•	•	•	•
Social	•	•	ø	●	ø	●	ø	ø	•	ø
Consistency	0.94	0.82	0.84	0.81	0.81	0.84	0.83	0.91	0.90	0.82
Raw coverage	0.09	0.28	0.08	0.07	0.07	0.06	0.08	0.09	0.08	0.12
Unique coverage	0.02	0.20	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.02
Overall solution consistency	0.83									
Overall solution coverage	0.43									

Note: ● = presence of core causal condition, • = presence of contributing causal condition; Ø = core causal condition is absent; ø = contributing causal condition is absent; blank spaces = "don't care" which implies that the causal condition may be present or absent; correspondingly raw and unique coverage indicate 'the share of the outcome … explained by a certain alternative path' and the 'share of the outcome … exclusively explained by a certain alternative path (Raw coverage indicates 'which share of the outcome is explained by a certain alternative path' (Wagemann and Schneider, 2007, p. 7).

To test for predictive validity, the data are randomly split (fifty-fifty) into a modeling and a hold-out sample (Mourad and Valette-Florence, 2016). The raw coverage and consistency results in Table 4 are very similar and meet accepted benchmarks.

Table 4: fsQCA Intermediate solutions for modeling and hold-out samples

	Causal conditions		Solution	
	Frequency cutoff	Consistency	Raw coverage	Consistency
Modeling	1	.818	.405	.849
Hold-out	1	.803	.440	.833

Collectively, the above indicate that multiple media use is not consistently related to the dimensions of the P-MMU and confirm the stability of such a finding. We proceed to further examine the nature and structural composition of the observed asymmetry or heterogeneity in the functional relationships.

5.2. Testing the research model

5.2.1. Measurement model

With the smallest and largest factor loadings being .742 and .955, the operationalizations of the P-MMU dimensions meet the commonly accepted benchmark of .70. All composite reliability (ρ_c) and average variance extracted (AVE) indices exceed the corresponding benchmarks of .70 and .50 (Fornell and Larcker, 1981). With the square root of each construct's AVE being notably higher than its bivariate correlations with the other constructs (Fornell and Larker, 1981) and none of the heterotrait-monotrait ratio inference values greater than .85 ($HTMT_{inference}$), discriminant validity is confirmed. All scale items with their respective psychometric indices, factor and cross loadings are presented in Appendix 1.

5.2.2. Structural Model

Testing of the structural model as a single segment reveals moderate explanatory power (R^2 = .239). There is no evidence of collinearity between the P-MMU dimensions (all VIF values below 5), and predictive relevance is confirmed ($Q^2 > 0$). The RMSR value of 0.052 is below the recommend 0.10 benchmark, however the $d_{UL}S$ and d_{G1} indexes are outside their respective confidence intervals (in square brackets). Five of the nine dimensions of the P-MMU are significant determinants of multitasking (Table 5). With the exception of gratification, the significant dimensions have a positive impact on multiple media use. To test the predictive validity of the solution, adhering to recommendations in Carrión, Henseler, Ringler and Roldán (2016), training and hold-out samples are constructed. Using randomization and guided by Steckel and Vanhonacker (1993), the training and hold-out samples respectively comprise 219 and 96 cases. The similarity of the R^2 values for the training (0.230) and hold-out (0.296) samples confirms predictive validity.

Table 5: The impact of the MMU dimensions on multiple media use

Dimensions of the P-MMU	Standardized regression coefficients	T statistics	Collinearity (VIF)
Assimilation	.124	1.75*	2.29
Comfort	.190	2.51**	2.33
Compulsive	.217	3.88***	1.49
Convenience	.064	0.95	2.42
Effectiveness	-.089	1.24	1.76
Gratification	-.155	1.79*	3.03
Information	-.073	0.99	2.37
MMC preference	.007	0.10	2.78
Social	.309	4.86***	2.03
R^2 = .239		d_{ULS} = 1.783 [.462, .840]	
Q^2 = .209		d_{G1} = 1.725 [.999, 1.570]	
SRMR = .052			

Note: * $p < .05$, ** $p < .01$ and *** $p < .001$

5.3. Identifying unobserved heterogeneity

5.3.1. Determine configuration (number of segments): FIMIX-PLS

Following recommendations in Hair *et al.* (2018, p. 182), results are obtained for different segment number solutions and their fit indexes are presented in Table 6. Sarstedt *et al.* (2011) report on the efficacy of the indexes and the general rule is (a) that 'the optimal solution is the number of segments with the lowest value' (Matthews, 2016, p. 212) and (b) that the normed entropy statistic (EN) should be greater than 0.50 (Hair et al., 2016, p. 69). The lowest value of MDL_5 is for one segment, however, given that this index is found to 'show pronounced underestimation tendencies' (Hair et al., 2016, p. 69) is an indication of existence of two or more segments. Given that the two segment solution fails to meet either of the above criteria, we focus on the results for the three and four segment solutions. Unfortunately, jointly considering AIC_3 (four segments) and CAIC (three segments) leads to differential solutions and the same applies to the two best performing criteria of AIC_4 (four segments) and BIC (three segments). Considering, (a) that AIC 'often over specifies the correct number of segments' (Hair *et al.*, 2016, p. 69), (b) that the improvement in AIC and AIC_3, and AIC_4 between three and four segment solutions is small, and (c) analytical problems due to low size of segment four (Hair et al., 2016, p. 70), a three segment solution is adopted which results in segments sizes of 150, 99 and 66 respondents.

Table 6: FIMIX-PLS - Fit indices and relative sizes for one to four segment solutions

	Number of segments			
Criteria	1	2	3	4
AIC	827.861	799.794	688.927	**651.592**
AIC_3	837.861	820.794	720.927	**694.592**
AIC_4	847.861	841.794	752.927	**737.592**
BIC	865.386	878.598	**809.009**	812.953
CAIC	875.386	899.598	**841.009**	855.953
MDL_5	**1,095.49**	1,361.81	1,545.34	1,802.40
EN		0.429	0.615	0.719
Relative segment size		1 = .63 2 = .37	1 = .48 2 = .31 3 = .21	1 = .45 2 = .28 3 = .18 4 = .09

Note: Bold values denote optimal configuration.

The segmentation of respondents has a notable impact on the explanatory power of the model, as shown in Table 7. The R^2 of each segment, especially for segments 2 and 3 (substantial) and the weighted average (moderate), are higher than the full dataset. These results provide a strong indication of sample heterogeneity.

Table 7: FIMIX-PLS – R^2 values

	Full dataset	Segment 1	Segment 2	Segment 3	Weighted Average
P-MMU	.239	.294	.756	.982*	.582

Note: * The high R^2 value is attributed to very low dispersion in the dependent variable (the confidence interval of multiple media usage is 2.453 and 2.925).

5.3.2. Refining segment membership and segment-specific models: PLS-POS

Adopting the recommendation in Hair *et al.* (2018, p. 186-7), PLS-POS is applied using the solution from FIMIX-PLS as the starting point and 10 iterations are carried out. The search depth is equal to 315 (i.e., observations in the full data set) and maximization of the variance of the multiple media use variable is the optimization criterion. The solution with the highest objective value outcome (optimization of the sum of each group's sum of R^2 values; Becker *et al.*, 2013) is selected. The results in Table 8 confirm the psychometric properties of the constructs for each segment and the MICOM procedure verifies inter-segment measurement invariance (for reasons of brevity, the results for segment 1 and 2 are presented in Appendix 3, with full results available on request). The decline in the relative size of segment 1 (from 48% to 39%) is mainly 'compensated' by an increase in size of segment 3 (from 21% to 28%). In comparison with FIMIX-PLS, re-allocation of respondents improves the weighted R^2 and explanatory power for segment 1. We find marginal improvement in the R^2 of segment 1 and a reduction in the corresponding value of segment 3; however, all R^2 values are now substantial. The positive Q^2 values confirm predictive relevance for all segments, collinearity is not a concern and the RMSR, d_{ULS} and d_{G1} indicies meet criteria (with the exception of the RMSR for segment 3 and dULS for segment 2). The notable improvement compared to the one segment solution provides further evidence of underlying heterogeneity in the functional relationships between the P-MMU dimensions and multiple media use, and thus existence of distinct segments. Before proceeding to discuss the results, similar to Mourad and Valette-Florence (2016), discriminant analysis is applied to test the stability of the configuration. The corresponding predictive accuracy values for the original, cross-validation and hold-out samples are 76%, 65% and 64% and the Press Q statistic of 256 is significant; thus providing confidence in the solution.

The substantial differences in the pattern of pathway significance of each segment in comparison with the full data set, and also between the segments, re-confirm heterogeneity. The significant impact of assimilation ($\beta = .124$, $p < .05$) and social ($\beta = .309$, $p < .001$) on multitasking in the full dataset is due to segment 2 ($\beta_{assimilation} = .329$, $p < .001$; $\beta_{social} = .425$, $p < .001$), while for comfort, the full dataset significance ($\beta = .190$, $p < .01$) is due to segment 3 ($\beta = .586$, $p < .001$). Although compulsive is significant in the full dataset ($\beta = .217$, $p < .001$) and in each of the segments, differences are found in the sign of the relationships, i.e. for segment 1 compulsive has a negative ($\beta = -.324$, $p < .001$), while for segments 2 ($\beta = .668$, $p < .001$) and 3 ($\beta = .290$, $p < .001$), a positive impact on multitasking. Significant inter-segment differences indicate that the impact of compulsive is greatest in segment 2 and smallest in segment 3. The negative effects of gratification in the full dataset ($\beta = -.115$, $p < .05$) align with results from segments 1 ($\beta = -.674$, $p < .001$) and 2 ($\beta = -.359$, $p < .001$), while this dimension has no impact on multitasking in segment 3. In relative terms, gratification is a stronger (negative) determinant of multitasking in segment 1.

Although convenience, effectiveness, information and MMC preference are not significant when treating the data as homogeneous (i.e., full dataset), segmentation uncovers significance in one or more segments. Convenience is significant in segment 3 ($\beta = .494$, $p < .001$) and information in segment 1 ($\beta = .338$, $p < .01$). Opposing signs are found in the impact of effectiveness on multitasking between segments 1 ($\beta = .322$, $p < .001$) and 3 ($\beta = -.814$, $p < .001$), with effectiveness having a strong effect in segment 3. Finally, MMC preference has a positive impact on multitasking in segment 1 ($\beta = .842$, $p < .001$) and negative impact in segments 2 and 3 ($\beta = -.160$, $p < .05$; $\beta = -.199$, $p < .001$). In comparative terms, the impact of this dimension is highest for segment 1, while no significant difference is found in its impact between segments 2 and 3.

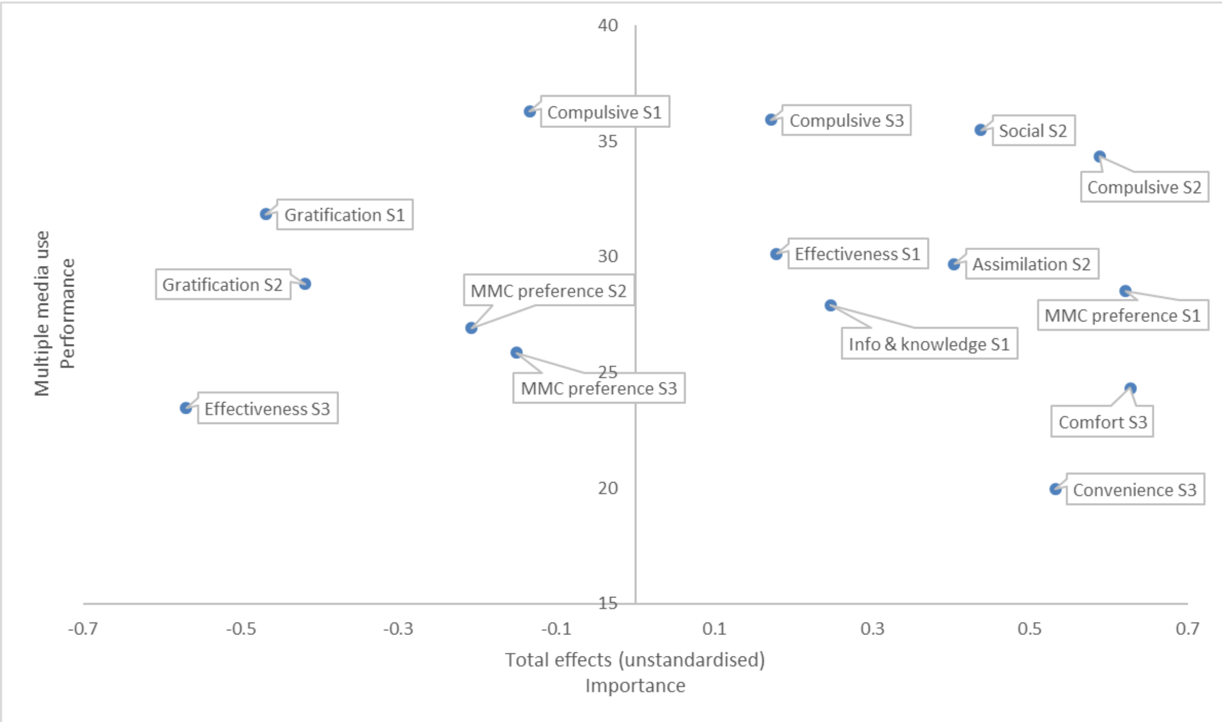
Table 8: PLS-POS solution

	Full dataset	Segment 1	Segment 2	Segment 3	Sing Δ seg1 – seg2[¥]	Sign Δ seg1 – seg3	Sign Δ seg2 – seg3
N (relative segment size - %)	315	124 (.39)	103 (.33)	88 (.28)			
Measurement model							
Composite reliability	+	+	+	+			
AVE (convergent validity)	+	+	+	+			
$HTMT_{inference}$ (discriminant validity)	+	+	+ (MMC preference .859)	+			
Collinearity	+	+	+	+			
Structural model	Standardized regression coefficients (t statistics)						
Assimilation	.124 (1.75)*	-.203 (1.48)	.329 (3.24)***	-.096 (1.06)			
Comfort	.190 (2.51)**	.103 (0.83)	.099 (1.19)	.586 (7.11)***			
Compulsive	.217 (3.88)***	-.324 (2.20)*	.668 (9.01)***	.290 (4.59)***	***	***	***
Convenience	.064 (0.94)	-.121 (1.19)	-.110 (1.42)	.494 (6.28)***			
Effectiveness	-.089 (1.24)	.322 (3.58)***	-.056 (0.67)	-.814 (7.19)***		***	
Gratification	-.155 (1.79)*	-.674 (4.19)***	-.359 (3.14)***	-.152 (1.55)	*		
Information	-.073 (0.99)	.338 (2.85)**	.123 (1.53)	.112 (1.05)			
MMC preference	.007 (0.10)	.842 (5.55)***	-.160 (1.71)*	-.199 (2.56)**	***	***	ns
Social	.309 (4.86)***	.157 (1.39)	.452 (5.61)***	.037 (0.67)			
R^2	.239	.613	.763	.835			
Weighted R^2			.724				
Q^2	.209	.467	.707	.760			
SRMR	.052	.093	.074	.118			
d_{ULS}	1.783 [.462, .840]	5.798 [1.015, 13.149]	3.606 [1.183, 2.605]	9.291 [1.248, 21.407]			
d_{G1}	1.725 [.999, 1.570]	3.418 [2.097, 4.298]	3.528 [2.374, 5.337]	9.773 [4.056, 13.139]			

Note: * $p < .05$, ** $p < .01$ and *** $p < .001$; ¥ Formal tests only when coefficients for two segments are significant; Similar to Table 6 the R^2 values reflect low dispersion in the dependent variable: segment 1 - 2.276 to 2.554, segment 2 - 3.303 to 3.788 and segment 3 - 2.241 to 2.674.

The x-axis (importance) in Figure 3 denotes the importance of each P-MMU dimension in explaining multiple media use, while the y-axis (performance) presents the corresponding average scores. Focusing on the right hand side (high positive importance), Figure 3 shows that for segment 1, MMC preference dominates; for segment 2, compulsive, assimilation and social are the most valuable drivers of multiple media use; while for segment 3, comfort and convenience have the highest importance. The low performance of all the P-MMU dimensions means that there is room for improvement in all the dimensions. These results are developed in the discussion section of the paper.

Figure 3: Importance-Performance Map Analysis (IMPA)



Note: Only the significant functional relationships are included in the figure (Rigdon *et al.*, 2011); S1, S2 and S3 denote segments.

5.3.3. Profiling the segments

Having established the existence of heterogeneity, the next step involves identifying the underlying structure of (profiling) the segments. No significant association is found between segment membership and demographics (gender χ^2 = .083; age χ^2 = .098). Given previous mixed findings for gender, reported in the review of literature (Section 2), the lack of significant association is not surprising. Similarly, the absence of association between age groups and segment membership is plausible, due to the relatively narrow age group defined by the Digital Native sample. Of the two psychographic variables, ANOVA reveals significant differences for sensation seeking ($F_{2, 312}$ = 4.77, p = .009) consistent with previous studies (Duff *et al*., 2014; Jeong and Fishbein, 2007; Kononova, 2013; Yang and Zhu, 2016), but not for innovativeness ($F_{2, 312}$ = 1.71, p = .182). In the absence of supporting literature, it is speculated that this unexpected finding for innovativeness may be associated with the particular characteristics of the Digital Native sample. Mean values of sensation seeking for segments 1 (M = 3.72) and 3 (M = 3.58) are significantly higher compared to segment 2 (M = 3.19). Behavioral information in the forms of cross-media usage offers some insight. Significant associations are found between segment membership and five of the six cross-media combinations (Table 9), using adjusted standardized residuals to isolate the source of the association (Everitt, 1992). Of the three segments, segment 1 associates with fewer combinations of multiple media use (surfing the internet & texting most of the time and watching TV & texting some of the time). Although segments 2 and 3 associate with all the significant multiple media use combinations, their patterns of media multitasking are distinct. Segment 2 engages little or never with multiple media use, while segment 3 shows varied media multitasking behavior. Respondents in segment 3 engage extensively (most of the time) in: surfing the internet & texting; surfing the internet & use of social media and texting & use of social media, showing considerable engagement in TV watching & use of social media (some of the time) and no interest in combining texting & TV watching (never).

Table 9: Segment membership and cross-media use

	Surfing the internet & Texting χ^2 = 37.96; sig = .000	Surfing the internet & TV watching χ^2 = 9.26; sig = .160	Surfing the internet & Social media χ^2 = 25.72; sig = .000	Texting & TV watching χ^2 = 30.64; sig = .000	Texting & Social media χ^2 = 43.66; sig = .000	TV watching & Social media χ^2 = 27.78; sig = .000
Segment 1	Most of the time			Some of the time		
Segment 2	Little of the time or Never		Never	Little of the time	Little of the time or Never	Little of the time
Segment 3	Most of the time		Most of the time	Never	Most of the time	Some of the time

One way ANOVA and appropriate post hoc analysis on the latent mean scores reveal significant differences between the three segments in six of the nine MMU dimensions (Table 10). In comparative terms, segment 1 shows preference for information, segment 2 for assimilation and social, while comfort, convenience, effectiveness and information are highest for segment 3. Finally, there are no significant differences amongst the three segments in the mean values of compulsive, gratification and MMC preference.

Table 10: ANOVA results

	F, Sig. (for all tests $df_1 = 2$ and $df_2 = 312$)	Group 1	Group 2
Assimilation	3.716, 0.018	$M_2 = 4.47$	$M_1 = 4.08$, $M_3 = 4.06$
Comfort	3.953, 0.010	$M_3 = 5.07$	$M_1 = 4.79$, $M_2 = 4.75$
Compulsive	0.142, 0.868	$M_1 = 3.82$, $M_2 = 3.94$, $M_3 = 3.84$	
Convenience	3.209, 0.021	$M_3 = 4.91$	$M_1 = 4.77$, $M_2 = 4.61$
Effectiveness	2.627, 0.037	$M_3 = 4.59$	$M_1 = 4.19$, $M_2 = 4.23$
Gratification	0.822, 0.441	$M_1 = 4.09$, $M_2 = 4.28$, $M_3 = 4.27$	
Information	3.614, 0.014	$M_3 = 4.36$, $M_1 = 4.33$	$M_2 = 4.00$
MMC preference	0.441, 0.644	$M_1 = 4.37$; $M_2 = 4.44$; $M_3 = 4.51$	
Social	2.907, 0.028	$M_2 = 3.88$	$M_1 = 3.42$, $M_3 = 3.45$

6.0 Discussion

Previous studies describe audience characteristics (for example, Carrier et al., 2009; Srivastava *et al.,* 2016; Segijn *et al.,*2017), identify media combinations (for example, Carrier *et al*., 2015; Pilotta and Shultz, 2005; Segijn *et al.,* 2017) and examine selected personal traits and motivations associated with multiple media use (for example, Bardhi *et al.,* 2010; Jeong and Fishbein, 2007; Duff *et al*., 2014; Kononova and Chiang, 2015; Srivastava *et al.,* 2016). Earlier in the paper, questions are raised about the explanatory and predictive power of the above studies and polychronicity is identified as a theoretically grounded concept that has potential to overcome the identified limitations. However, only three studies examine the role of polychronicity on multiple media use (Kononova and Chiang, 2015; Rubenking, 2016; Srivatsava *et al.,* 2016). Despite their merits and the insights gained from these investigations, concerns are expressed in terms of: (a) the use of a general scale in the operationalization of polychronicity, (b) treating polychronicity as a unidimensional construct and (c) the single behavior treatment of multiple media use. The first two of the above are addressed through the use of a multiple media specific scale (the P-MMU), whose relationship with multiple media use is examined at dimensional level, while the application of the MMI measure addresses the third concern. In addition, on the grounds of recent research that questions the symmetric behavior of functional relationships and indicates considerable heterogeneity in the structure and nature of such relationships; the need for examination of the existence of underlying groups of segments is suggested. Briefly, the results indicate existence of asymmetry in the functional relationships between the dimensions of polychronicity and multiple media use and reveal the presence of distinct segments. As hypothesized, differential structures of multiple media use help to explain the composition of the segments.

6.1 Theoretical contributions

The P-MMU scale demonstrates acceptable explanatory and predictive powers and five of its nine dimensions are significant determinants of multiple media use. At a general level, these findings align with the contention in consumer behavior theory that preference precedes behavior (Lavidge and Steiner, 1961) and support previous results (Kononova and Chiang, 2015; Rubenking, 2016; Srivastava *et al.,* 2016). However, not all the goodness of fit measures meet accepted benchmarks and, contrary to expectations, one of the dimensions has a negative effect on multiple media use. Confirmation of asymmetric impact of the P-MMU dimensions on multiple media use led to the identification of considerable heterogeneity in the behavior and nature of the functional relationships. Portioning respondents into three segments resulted in substantial improvements in model fit, and identified that although all the P-MMU dimensions are significant determinants of multiple media use; their impact differs notably between segments. Theoretically, this study provides evidence of the relevance of individuals' preferences in the formation of multiple media use and illustrates heterogeneity in the effects of different preference dimensions on such media use. These findings represent an important contribution to subject knowledge; they imply that omitting to account for such heterogeneity can lead to theoretical mismatch (resulting from ignoring the underlying complexity of the preference-to-behavior relationship). Consequently, future researchers should account for the effects of different preference configurations when examining multiple media behavior. To the best of the authors' knowledge, this is the first study to examine the effects of the dimensions of preference in relation to multiple media use, and the first empirical investigation that demonstrates heterogeneity in this relationship. Although previous studies have identified preference in relation to media multitasking (Kononova and Chiang, 2015; Rubenking, 2016; Srivatsava *et al.,* 2016), this study demonstrates the need for a multi-dimensional conceptualization of preference in the examination of this complex behavioral phenomenon.

Focusing on the uncovered structures, our analysis reveals three segments; each emphasizing a different set of preference dimensions for its' multiple media use. ANOVA reveals significant differences between these segments (Table 10). A comparison of the segments reveals that a preference for information is indicated in Segment 1; assimilation and social in Segment 2; with Segment 3 showing preferences for comfort, convenience, effectiveness and information (although information is not a determinant of multiple media use in this segment). This typology, entitled the Multiple Media User Typology (MMU-T), comprises segments named as: 'Information seekers'; 'Connected' and 'Instinctives'. Summarising the information in Table 8, the significant preference dimensions for each segment are portrayed in Table 11. Closer examination reveals differential patterns in terms of (a) pattern of impact (for example, 'MMC preference' and 'Compulsive' appear in all segments, while 'Information' is a significant determinant only in the 'Information seekers' segment), and (b) sign of effect (for example, 'Compulsive' has a negative effect in the 'Information seekers' segment, but a positive effect in the 'Connected' and 'Instinctives' segments). Following earlier commentary, research that ignores the above can reach 'unsafe' conclusions; for example, in the case of 'Compulsive', failing to support a hypothesised relationship because of the opposing directions of the coefficients in different segments.

Table 11: The significant determinants of multiple media use

‘Information seekers’ (Segment 1)	‘Connected’ (Segment 2)	‘Instinctives’ (Segment 3)
Compulsive (-)	Assimilation (+)	Comfort (+)
Effectiveness (+)	Compulsive (+)	Compulsive (+)
Gratification (-)	Gratification (-)	Convenience (+)
Information (+)	MMC preference (-)	Effectiveness (-)
MMC preference (+)	Social (+)	MMC preference (-)

Note: (+) = positive significance (-) = negative significance

For Segment 1, the distinctive characteristics of preference for multiple media use are effectiveness and a wish to be efficient and get things done. A preference for instant access to information and knowledge to acquire different points of view is also significant. In addition, individuals in this segment prefer to switch between media and have multiple streams of stimulation. However, their preference for multiple media use is not driven by compulsion or emotional gratification. The dominance of the ‘effectiveness’, ‘information’ and ‘MMC preference’ dimensions guide the naming of this segment as ‘Information seekers’. For individuals in Segment 2, the preference for multiple media use is partially driven by a compulsion to multitask with media. Assimilation of media content is also a key determinant, with multiple media use helping to absorb and manage information. These individuals are also attracted to the social benefits of multiple media use, such as gaining a sense of belonging and connecting with friends and family. However, emotional gratification and a preference for switching between media are not significant determinants of their multiple media use. ‘Assimilation’, ‘compulsive’ and ‘social’ dimensions of polychronicity form the three main drivers of this segment’s preference to multitask with media, leading to the name ‘Connected’. The preference for multiple media use of Segment 3 is driven primarily by ’comfort with media multitasking’, ‘compulsive’ and ‘convenience’, leading to the ‘Instinctives’ label. Individuals in this segment are confident multitaskers and multiple media use comes naturally to them. ‘Instinctives’ preference is based on ease of navigation between media, on different devices and in different locations. Nevertheless, neither a preference for effectiveness and efficiency nor multi-media channels drives their behavior.

While extant literature reveals user typologies for assorted individual media forms (Brandtzaeg, 2010), such as Facebook (Shao, Ross and Grace, 2015), this study contributes the first known typology of multiple media users. The MMU-T reaches beyond simple classifications of media users by identifying the underlying reasons for their multiple media use. Although there is some debate about whether typologies are helpful, one plausible reason for the popularity of typologies is that they appear to provide a parsimonious framework for describing complex organizational forms. Typologists often achieve parsimony by providing elegant descriptions of their typologies and glossing over the complex processes that determine the focal organizational outcomes. However, using the functional relationships between preference (in the form of polychronicity) and behaviour (multiple media use) as the analytical unit; the proposed MMU-T typology overcomes such criticism, providing a notable contribution to the understanding of multiple media use. Furthermore, these findings support previous literature, which demonstrates the heterogeneity of preference in the marketing context (for example, Kamakura, Kim and Lee, 1996).

An examination of the underlying structure of the segments is enabled by profiling the 'Information seekers', 'Connected' and 'Instinctives'. A detailed summary of each segment, its dominant polychronicity dimensions and selected cross-media combinations is shown in Table 12.

Table 12: MMU-T segments (with preferences) and cross-media use

MMU-T Segment	Significant dimensions of polychronicity	Surfing the internet & Texting	Surfing the internet & Social media	Texting & TV watching	Texting & Social media	TV watching & Social media
'Information seekers' (Segment 1)	Compulsive (-) Effectiveness (+) Gratification (-) Information (+) *MMC preference (+)*	Most of the time		Some of the time		
'Connected' (Segment 2)	*Assimilation (+)* *Compulsive (+)* Gratification (-) MMC preference (-) *Social (+)*	Little of the time or never	Never	Little of the time	Little of the time or never	Little of the time
'Instinctives' (Segment 3)	*Comfort (+)* Compulsive (+) *Convenience (+)* Effectiveness (-) MMC preference (-)	Most of the time	Most of the time	Never	Most of the time	Some of the time

Italics denote the most dominant preferences in each MMU-T segment (from IMPA Figure 3)

'Information seekers' are highly selective multiple media users, associating with the fewest media combinations. They focus almost exclusively on 'surfing the internet & texting', only 'TV watching & texting' some of the time. 'Information seekers' multiple media choices are in line with their most dominant characteristic, a preference for multi-media channel use. Furthermore, their desires for 'information and knowledge' and 'effectiveness and efficiency' also align with their limited cross-media choices. 'Connected' spend the least time engaged in multiple media use, but the little time they do spend aligns closely with their desire to stay connected. Individuals in this segment consider their multiple media use to be driven by compulsion; in addition, they value multiple media use in order to assimilate media content and gain associated social benefits. Media combinations include those which allow social connections, such as 'texting & social media' and 'TV watching & social media'. The 'Instinctives'' multiple media use is predominantly driven by their comfort with media multitasking and the associated feeling that such behavior is convenient for them. This segment extensively engages in multiple media use, using several combinations 'most of the time'. Dominant combinations align with their comfort with multitasking, including: 'surfing the internet & texting'; 'surfing the internet & social media' and 'texting & social media'; with 'TV watching & social media' some of the time. Hence, the aforementioned drawback regarding previous studies' 'single behavior' treatment of multiple media use (Rubenking, 2016; Srivatsava *et al.,* 2016) is addressed in this study, with the confirmation that different segments reveal distinct multiple media usage patterns.

In summary, the knowledge gained from this study represents considerable progress towards an enhanced appreciation of why individuals' multitask with media, providing a notable step towards an understanding of the foundations of multiple media use. Specific contributions to subject knowledge include: a typology of multiple media users; the determination of the drivers of multiple media use on which the three segments are based and the identification of distinct patterns of multiple media use among 'Information seekers', 'Connected' and 'Instinctives'.

6.2 Managerial implications

For practitioners involved in the planning of multi-media advertising campaigns, these findings provide important insights. In pursuing effective and efficient campaign outcomes, the concepts of reach and frequency are important guiding principles for media planners. A central tenet of the planning process is the optimum selection of media channels; to gain maximum exposure and impact, among selected target audiences, at minimum cost (Danaher, 2007; Fill and Turnbull, 2016; Taylor *et al*., 2013). The availability of a new planning tool in the guise of an empirically derived typology of multiple media users provides valuable practical benefits for planners of multi-media campaigns. In particular, the MMU-T could be used to increase the accuracy of targeting among multiple media users, thus maximizing reach among the elusive Digital Native audience.

From a multi-media planning perspective, of the three segments in the MMU-T, the 'Instinctives' appear the most appealing segment (among the Digital Native audience); using the majority of media combinations 'most or some of the time'. 'Information seekers' are more selective in their chosen combinations of multiple media use, using just two of the combinations 'most or some of the time'; while 'Connected' use several combinations, but only a 'little of the time'. As an integral part of the media planning process, the power of the MMU-T comes to the fore once top level media channel choices are determined, to enhance the specificity of reach among the target audience. For example, in a campaign planning scenario for a new mainstream film release aimed at a Digital Native audience, combining television, internet and social media; the 'Instinctives' are revealed as the most appropriate segment for targeting purposes (associating 'some of the time' with a combination of 'TV watching & social media' and most of the time with 'surfing the internet & social media) (Table 12). In this way, through the choice of appropriate media vehicles to gain the attention of the 'Instinctives' audience; the synergistic benefit of this tri-media combination is optimized. 'Connected' could also be considered, although they associate with combinations of 'TV & social media', 'surfing the internet & texting' and 'surfing the internet social media' only a 'little of the time'. However, in this particular multi-media scenario, the 'Information seekers' are not considered an appropriate target segment.

In striving to match the most appropriate media channels to target audiences effectively and efficiently, a range of syndicated industry media research sources are routinely analyzed by media planners (providing basic demographic, brand and media information for a designated target audience). Yet, these syndicated sources are often criticized by media practitioners for providing data which is too general (Percy and Rosenbaum-Elliott, 2016). The specific and detailed understanding of the underlying preferences of the segments of the MMU-T among the Digital Native audience examined in this study provides a superior multi-media planning resource. For example, in the aforementioned campaign planning scenario combining television, internet and social media, syndicated industry media research sources would supply basic general planning information for each medium; but in addition, the specific in-depth understanding of the underlying preferences of the 'Instinctives' (as the chosen target segment) should be adopted by media planners. Accordingly, the application of an increased level of specificity and detail at this stage of the media planning process allows enhanced efficacy in reaching this target audience.

Media planning guidelines are explicitly informed by the IMPA (Figure 3, Section 5.3.2). Returning to the above-mentioned film release scenario and guided by Figure 3; the knowledge that the

‘Instinctives’ (S3) preference for multiple media use is primarily driven by ‘comfort with multiple media use’ and ‘convenience’ (featuring the ease of navigation between media on portable devices in different locations) is valuable in the selection of effective combinations of television, internet and social media channel opportunities from the extensive range available. For example, such preference dimensions would indicate the consideration of channels available on mobile media platforms, maximizing the influence of the indicated preference determinants. Similarly, in a campaign planning scenario for an alternative brand, in which the ‘Information seekers’ (S1) are identified as the key target; ‘MMC preference’ is the dominant dimension, which would specifically advocate a multi-media channel campaign. Likewise, if the ‘Connected’ (S2) segment were the identified target, media planners should concentrate on ‘social’, ‘compulsive’ and ‘assimilation’ dimensions (Figure 3). Such preferences would suggest the use of social media channels such as Facebook and Instagram. Hence, to increase the accuracy of media channel planning, the consideration of these detailed IMPA guidelines is recommended (in addition to conventional media research data sources), to maximize exposure and impact among a Digital Native audience.

In summary, the central practical impacts of this study are twofold: (a) the provision of an empirically derived typology, the MMU-T, for media planners attempting to match cross-media combinations to a Digital Native target audience effectively and efficiently; and (b) the in-depth understanding provided by the significant dimensions of ‘Information seekers’, ‘Connected’ and ‘Instinctives’, as a supplementary media planning resource. These contributions provide media planners with a valuable new resource, for application in their on-going search for optimum media schedules, to capture the synergistic benefits of multi-media campaigns among multiple media users. While this initial study focusses entirely on the Digital Native audience, it is envisaged that future work will examine alternative audiences.

6.3 Limitations and future research

This study contains a number of limitations. The data collection method depended on an opt-in panel, administered by a professional list broker; which, however well managed, cannot control or test for sample bias or non-response. A cross-sectional self-report questionnaire was used, which can result in systematic sequence bias. Although issues associated with randomization cannot be eliminated; to reduce such bias, appropriate procedures were introduced, such as the randomization of scale items and dimensions of polychronicity during the survey.

The sample for this study comprised Digital Natives (born after 1980), confirmed in the literature as the most prevalent multiple media users. Future studies should include alternative groups; for example, Digital Immigrants (born before 1980), to determine whether the criteria linking the dimensions of polychronicity and multiple media use remain the same (or differ). In this investigation, data were collected for two-way media combinations (for example, a combination of TV and surfing the internet), but future work should go further to include prevalent three-way combinations of multiple media use such as TV, surfing the internet and social media. The scope of this study was confined to the U.K., whereas future empirical work should investigate different countries with inherent variations in culture, media concentration and technological development.

While this study has made a valuable contribution to knowledge regarding the differential impact of the dimensions of polychronicity on multiple media use, to progress the understanding of why individuals engage in multiple media use further research is needed. Polychronicity (represented by the context specific P-MMU scale) should be embedded into a nomological model. In addition to the dimensions of polychronicity, known antecedents from previous empirical studies should be included. For example: media ownership (Kononova and Chiang, 2015; Segijn *et al.,* 2017); media access (Jeong and Fishbein, 2007; Wang and Tchernev, 2012); age (Carrier et al., 2009); gender (Jeong and Fishbein, 2007; Duff et al., 2014) and selected personal traits such as sensation seeking (Duff et al., 2014; Yang and Zhu, 2016).

7.0 References

AGARWAL, R. and PRASAD, J. “A conceptual and Operational Definition of Personal Innovativeness in the Domain of Information Technology.” *Information Systems Research*, 9, (1998): 204-215.

AJZEN, I. and FISHBEIN, M. “Attitude-behaviour relations: a theoretical analysis and review of empirical research.” *Psychological Bulletin* 84 (1977): 888-918.

AJZEN, I. and FISHBEIN, M. “*Understanding Attitudes and Predicting Social Behavior*.” Engelwood Cliffs, NJ, Prentice Hall, 1980.

AJZEN, I. “The Theory of Planned Behaviour.” In Locke, E.A. (ed.) *Organisational Behaviour and Human Decision Processes* 50 (1991): 179-211.

ALI, M., KAN, K.A.S. and SARSTEDT, M. “Direct and configurational paths of absorptive capacity and organizational innovation to successful organizational performance,” *Journal of Business Research*, 69 (2016): 5317-5323.

BARDHI, F., ROHM. A.J. and SULTAN, F. “Tuning in and tuning out: media multitasking among young consumers.” *Journal of Consumer Behavior 9* (2010): 316-332.

BECKER, J.-M., RAI, A., RINGLE, C.M. and VOLCKER, F. “Discovering Unobserved Heterogeneity in Structural Equation Models To Avert Validity Threats,” *MIS Quarterly*, 37(3), (2013): A3-A7.

BRANDTZAEG, P.B. “Towards a unified Media-User Typology (MUT): A meta-analysis and review of the research literature on media-user typologies.” *Computers in Human Behavior* 26 (2010): 940-956.

BRASEL, S.A. and GIPS, J. “Media Multitasking Behaviour: Concurrent Television and Computer Usage.” *Cyber Psychology, Behaviour and Social Networking 14*, 9 (2011): 527-534.

CARRIER, L.M., CHEEVER, N.A., ROSEN, L.D., BENITEZ, S. and CHANG, J. “Multitasking across generations: Multitasking choices and difficulty ratings in three generations of Americans.” *Computers in Human Behaviour 25* (2009): 483-489.

CARRIER, L.M., ROSEN, L. D., CHEEVER, N.A. and LIM, A.F. “Causes, effects and practicalities of everyday multitasking.” *Developmental Review* 35 (2015): 64-78.

CARRION, G.C., HENSELER, J., RINGLER, C.M. and ROLDAN, J.L. “Prediction-orientated modeling in business research by means of PLS path modeling: Introduction to a JBR special section,” *Journal of Business Research*, 69 (2016):4545-4551.

CONTE, J.M. and GINTOFT, J.N. “Polychronicity, Big Five Personality Dimensions, and Sales Performance.” *Human Performance* 18, 4 (2005): 427-444.

DELBRIDGE, K.A. *Individual differences in multitasking ability: Exploring a nomological network.* Unpublished Doctoral dissertation, Mitchigan State University, East Lansing, 2000.

DEVERS, K. J., LALLEMAND, N.C., BURTON, R.A., KAHWATI, L., McCALL, N. and ZUKERMAN, S., "Using Qualitative Comparative Analysis (QCA) To Study Patient Centered Medical Homes", Washington, D.C.: Urban Institute and RTI International, (2013) http://www.urban.org/research/publication/using-qualitative-comparative-analysis-qca-studypatient-centered-medical-homes

DANAHER, P. "Media Planning." In: *The Sage Handbook of Advertising.* Edited by Tellis, G.J. and Ambler, T., London: Sage, 2007.

DUFF, B., YOON, G., WANG, Z. and ANGHELCEV, G. "Doing It All: An Exploratory Study of Predictors of Media Multitasking." *Journal of Interactive Advertising* 14, 1 (2014): 11-23.

ENOCH, G. and JOHNSON, K. "Cracking the Cross-Media Code. How to use Single-Source Measures to examine Media Cannibalisation and Convergence." *Journal of Advertising Research* Jun, 50, 2 (2010): 125-136.

EVERITT, B.S. *The Analysis of Contingency Tables*, 2nd ed., London: Chapman and Hall, 1992.

FILL, C. and TURNBULL, S. *Marketing Communications – discovery, creation and conversations*. 7th Edition. Harlow: Pearson Education, 2016.

FOEHR, U.G. (2006) "Media Multitasking Among American Youth: Prevalence, predictors and pairings." Available at: http://faculty.ithaca.edu/jpowers/docs/SenSemReadings/mediamultitasking.pdf (Accessed 26 June 2013)

FORNELL, C. and LARKER, D.F "Evaluating structural equation models with unobservable variables and measurement error." *Journal of Marketing Research* 18 (1981): 39-50.

GRAWITCH, M.J. and BARBER, L.K. "In Search of the Relationship between Polychronicity and Multitasking Performance. The importance of Trait Self-control." *Journal of Individual Differences* 34, 4 (2013): 222-229.

HAIR, J.F. JR., SARSTED, M., MATTHEWS, L.M. and RINGLE, C.M. "Identifying and treating unobserved heterogeneity with FIMIX-PLS: part I – method." *European Business Review* 28, 1 (2016): 63-76.

HAIR, J.F. JR., SARSTEDT, M., RINGLE, C.M. and GUDERGAN, S.P. *Advanced Issues in Partial Least Squares Structural Equation Modeling*, London:Sage Publications, (2018).

HAIR, J.F. JR., HULT, G.T.M., RINGLE, C.M. and SARSTEDT, M. "*A Primer on Partial Least Squares Structural Equation Modeling." (PLS-SEM)*, 2nd ed., London:Sage Publications, (2017).

HALEY, R. I., "Benefit Segmentation: A decision-oriented research tool." *Journal of Marketing,* 32 (3), (1968): 30-35.

HOYLE, R.H., STEPHENSON, M.T., PALMGREEN, P., LORCH, E.P. and DONOHEW, R.L. "Reliability and validity of a brief measure of sensation seeking." *Personality and Individual Differences* 32 (2002): 401-414.

HWANG, Y., KIM, H. and JEONG, S-H. "Why do media users multitask? Motives for general, medium specific and content specific types of multitasking." *Computers in Human Behavior* 36 (2014): 542-548.

JEONG, S-H. and FISHBEIN, M. "Predictors of Multitasking with Media: Media Factors and Audience Factors." *Media Psychology* 10, 3 (2007): 364-384.

KAMAKURA, W.A., KIM, B-D. and LEE, J. "Modeling Preference and Structural Heterogeneity in Consumer Choice." *Marketing Science* 15, 2 (1996): 152-172.

KENT, R. *"Using fsQCA: Brief Guide and Workshop for Fuzzy-Set Qualitative Comparative Analysis,"* http:// hummedia.manchester.ac.uk/institutes/cmist/archive-publications/working-papers/2008/2008-10-teaching-paper-fsqca.pdf

KÖNIG, C.J. and WALLER, M.J. (2010) "Time for reflection: A critical examination of polychronicity." *Human Performance* 23 (2010): 173-190.

KONONOVA, A. Multitasking across borders: A cross-national study of media multitasking behaviors, its antecedents, and outcomes. *International Journal of Communication* 7 (2013): 688-710.

KONONOVA, A. and CHIANG, Y-H "Why do we multitask with media? Predictors of media multitasking among Internet users in the United States and Taiwan." *Computers in Human Behavior* 50 (2015): 31-41.

LAVIDGE, R.J. and STEINER, G.A. "A model for predictive measurements of advertising effectiveness." *Journal of Marketing* 25, October (1961): 59-62.

LEE, L., AMIR, O. and ARIELY, D. "In Search of Homo Economicus: Cognitive Noise and the Role of Emotion in Preference Consistency." *Journal of Consumer Research* 36, August (2009): 173-187.

LIN, L. "Breadth-Biased versus Focused Cognitive Control in Media Multitasking Behaviours." *Proceedings of the National Academy of Sciences of the United States of America 106,* 37 (2009): 15521-15522.

LINDQUIST, J.D. and KAUFMAN-SCARBOROUGH, C. "The Polychronic-Monochronic Tendency Model PMTS scale development and validation." *Time and Society*, 16 (2/3) (2007): 253-285.

LLEWELLYN, D.J. WILSON, K.M. "The controversial role of personality traits in entrepreneurial psychology", *Education + Training*, 45 (6), (2003) pp.341-345.

MAGEN, H. "The relations between executive functions, media multitasking and polychronicity." *Computers in Human Behavior* 67 (2017): 1-9.

MATTHEWS, L.M., SARSTEDT, M., HAIR, J.F. JR. and RINGLE, C.M. "Identifying and Treating Unobserved Heterogeneity with FIMIX-PLS: Part II – A case study." *European Business Review* 28, 2 (2016): 208-224.

MOURAD, S. and VALETTE-FLORENCE, P. "Improving prediction with POS and PLS consistent estimations: An illustration," *Journal of Business Research*, 69 (2016): 4675-4684.

OPHIR, E., NASS, C. and WAGNER, A.D. Cognitive control in media multitaskers. *Proceedings of the National Academy of Sciences of the United States of America* 106, 37 (2009); 15583-15587.

PALMER, D.K. and SCHOORMAN, F.D. "Unpacking the multiple aspects of time in polychronicity." *Journal of Managerial Psychology* 14 (1999): 323-345.

PERCY, L. and ROSENBAUM-ELLIOTT, R. "*Strategic Advertising Management*." 5th Ed. Oxford: University Press (2016).

PILOTTA, J.J., SHULTZ, D., DRENIK, G. and RIST, P. “Simultaneous media usage: a critical consumer orientation to media planning.” *Journal of Consumer Behaviour* 3, 3 (2004): 285-292.

PILOTTA, J. J. and SHULTZ, D. “Simultaneous Media Experience and Synesthesia.” *Journal of Advertising Research* 45, 1 (2005): 19-26.

PRENSKY, M. “Digital Natives, Digital Immigrants.” *On the Horizon,* 9, 5 (2001): 1-6. Available from: http://www.marcprensky.com/writing/Prensky%20-%20Digital%20Natives,%20Digital%20Immigrants%20-%20Part1.pdf [Accessed: 26 March 2013].

RAGIN, C.C. “Qualitative Comparative Analysis Using Fuzzy Sets (FsQCA)”. In: B.Rihoux and C.C. Ragin (eds), *Configurational Comparative Methods: Qualitative Comparative Analysis (QCA) and Related Techniques*, (2008): 87-121, Applied Social Research Methods Series, volume 51, London:Sage Publications Ltd.

RAGIN, C. C. *“User's Guide to Fuzzy-Set/Qualitative Comparative Analysis 3.0.”* Irvine, California: Department of Sociology, University of California (2017).

RIGDON, E.E., RINGLE, C.M., SARSTEDT, M., and GUDERGAN, S.P. “Assessing heterogeneity in customer satisfaction studies across industry similarities and within industry differences,” In M. Sarstedt, M. Schwaiger, C.R. Taylor (eds.), *Measurement and Research Methods in International Marketing (Advances in International Marketing,* 22 (2011)*,* Emerald Group Publishing Limited, pp.169 – 194.

RINGLE, C.M., and SARSTEDT, M. “Gain more insight form your PLS-SEM results”. *Industrial Management & Data Systems*, 116(9) (2016): 1865-1886.

RINGLE, C.M., WENDE, S. and BECKER, J-M. (2015), *SmartPLS3*, Bönningstedt: SmartPLS. Retrieved from http://www.smartpls.com

ROBINSON, H.R. “Towards an enhanced understanding of the behavioural phenomenon of multiple media use.” *Journal of Marketing Management* 33, 9-10 (2017a): 699-718.

ROBINSON, H.R. “Individuals' preference for multiple media use - underlying motives.” *Qualitative Market Research: An International Journal*, 20(4) (2017):435-451.

ROBINSON, H.R. and KALAFATIS, S.P. “The ‘Polychronicity – Multiple Media Use’ (P-MMU) scale: a multit-dimentional scale to measure polychronicity in the context of multiple media use.” *Journal of Marketing Management* 33, 17-18 (2017):1421-1442.

ROSEN, L.D., CARRIER, L.M. and CHEEVER, N.A. “Facebook and texting made me do it: Media induced task switching while studying.” *Computers in Human Behavior 29* (2013): 948-958.

RUBENKING, B. “Multitasking with TV: Media Technology, Genre and Audience Influences.” *Communication Research Reports*, 33 (4) (2016); 324-331.

SARSTEDT, M., BECKER, J.-M., RINGLE, C.M. and SCHWAIGER, M. “Uncovering and treating unobserved heterogeneity with FIMIX-PLS: which model selection criterion provides an appropriate number of segments”, *Schmalenbach Business Review,* 63(1) (2011):34-62.

SARSTEDT, M., RINGLE, C.M. and HAIR, J.F. “Treating Unobserved Heterogeneity in PLS-SEM: A Multi-method Approach,” In: H. Latan and R. Noonan (eds) *Partial Least Squares Path Modeling*, (2017): 197-217, Heidelberg: Springer.

SEGIJN, C.M., VOORVELD, H.A.M., VANDERBERG, L., PENNEKAMP, S.F and SMIT, E.G. “Insight into everyday media use with multiple screens.” *International Journal of Advertising*, 36 (5) (2017):779-797.

SHAO, W., ROSS, M. and GRACE, D. “Developing a motivation-based segmentation typology of Facebook users.” *Market Intelligence & Planning* 33, 7 (2015): 1071-1086.

SRIVASTAVA, J., NAKAZAWA, M. AND CHEN, Y. “Online, mixed and offline media multitasking: Role of cultural, socio-demographic, and media factors.” *Computers in Human Behavior* 62 (2016): 720-729.

TAYLOR, J., KENNEDY, R., MCDONALD, C., LARGUINAT, L., EL OUARZAZI, L. and HADDAD., N. “Is the Multi-media Platform Whole More Powerful Than Its Separate Parts? Measuring Sales Effects of Cross-Media Advertising.” *Journal of Advertising Research* 53, 2 (2013): 200-211.

VOORVELD, E.G., SEGIJN, C., KETELAAR, P. AND SMIT, E.G. “Investigating the prevalence and predictors of media multitasking across countries.” *International Journal of Communication.* 8 (2014): 2755-2777.

WEBSTER, J.G. and KSIAZEK, T.B. “The Dynamics of Audience Fragmentation: Public Attention in an Age of Digital Media.” *Journal of Communication* 62, 1 (2012): 39-56.

WAGEMANN, C., and SCHNEIDER, C.Q. “Standards of good practice in qualitative comparative analysis (QCA) and fuzzy-sets”. http://www.compasss.org/wpseries/WagemannSchneider2007.pdf (2007)

WANG, Z. and TCHERNEV, J.M. (2012) “The “Myth” of Media Multitasking: Reciprocal Dynamics of Media Multitasking, Personal Needs, and Gratifications.” *Journal of Communication* 62, 3 (2012): 493-513.

WOODSIDE, A. “Moving beyond multiple regression analysis to algorithms: Calling for a paradigm shift from symmetry to asymmetric thinking in data analysis, and crafting theory.” *Journal of Business Research*, 66 (2013):463-472.

WOODSIDE, A. “Visualizing·matching·generalizing: Case identification hypotheses and case-level data analysis.” *Australian Marketing Journal*, 23 (2015):246-258.

XU, L. “Impact of simultaneous collaborative multitasking on communication performance and experience. “ Document number.osu1218593084 http://rave.ohiolink.edu/etdc (2008)

YEYKELIS, L., CUMMINGS, J.J. and REEVES, B. “Multitasking on a single device: Arousal and the Frequency, Anticipation, and Prediction of Switching between Media Content on a Computer.” *Journal of Communication* 64 (2014): 167-192.

Appendix 1:

P-MMU Scale items, factor (bold) and cross loadings

Dimensions of the P-MMU	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Assimilation [1]									
Media multitasking helps me to filter media content	**0.923**	0.401	0.332	0.477	0.453	0.518	0.637	0.487	0.423
Multitasking with media helps me to make sense of information	**0.897**	0.303	0.313	0.407	0.344	0.507	0.599	0.410	0.453
Multitasking helps me absorb the media bombarded at me	**0.921**	0.367	0.393	0.440	0.390	0.518	0.608	0.529	0.430
Media multitasking helps me to manage information	**0.942**	0.372	0.337	0.449	0.388	0.552	0.670	0.468	0.452
Comfort with MM [2]									
I feel comfortable when I am media multitasking	0.345	**0.906**	0.349	0.572	0.610	0.429	0.453	0.409	0.340
For me, multitasking with media is habitual behavior	0.358	**0.876**	0.285	0.654	0.472	0.456	0.379	0.464	0.287
Media multitasking is something which comes naturally to me	0.308	**0.843**	0.379	0.541	0.396	0.435	0.352	0.414	0.320
I'm just good at multitasking with media	0.377	**0.889**	0.345	0.601	0.526	0.440	0.379	0.449	0.292
Compulsive addictive [3]									
I feel a constant compulsion to multitask with media	0.360	0.356	**0.938**	0.340	0.255	0.492	0.324	0.485	0.420
Multitasking with media is compulsive	0.357	0.409	**0.955**	0.345	0.292	0.515	0.331	0.477	0.452
Media multitasking is addictive	0.342	0.334	**0.944**	0.343	0.243	0.482	0.293	0.446	0.376
Convenience [4]									

It is easy to navigate between media when I am multitasking	0.409	0.584	0.319	**0.849**	0.373	0.456	0.356	-0.224	0.507
Media multitasking is effortless with portable devices	0.409	0.584	0.319	**0.849**	0.373	0.460	0.356	0.507	0.295
Technology nowadays makes media multitasking effortless	0.415	0.534	0.341	**0.871**	0.308	0.452	0.309	0.580	0.353
It is easy to multitask with media in many different locations	0.426	0.558	0.297	**0.874**	0.340	0.470	0.353	0.523	0.323
Effectiveness and efficiency [5]									
I can get more done when I multitask with media	0.423	0.509	0.27	0.425	**0.913**	0.456	0.474	0.366	0.389
Multitasking with media makes me more productive	0.419	0.563	0.274	0.417	**0.962**	0.465	0.511	0.349	0.413
Media multitasking saves me time	0.401	0.498	0.277	0.352	**0.940**	0.406	0.512	0.319	0.37
Media multitasking helps me get things done quickly	0.354	0.531	0.221	0.366	**0.935**	0.404	0.468	0.342	0.368
Emotional gratification [6]									
Media multitasking is enjoyable	0.472	0.521	0.402	0.587	0.448	**0.842**	0.472	0.731	0.563
Media multitasking makes me feel good	0.428	0.264	0.409	0.324	0.272	**0.816**	0.322	0.591	0.559
I multitask with media to relax	0.507	0.416	0.48	0.423	0.350	**0.821**	0.426	0.538	0.480
Multitasking with media keeps me company	0.513	0.496	0.481	0.491	0.502	**0.899**	0.466	0.626	0.598
Information and knowledge [7]									
When media multitasking, I can get instant access to information	0.553	0.486	0.298	0.435	0.501	0.478	**0.742**	0.407	0.391
Media multitasking allows me to see the ‘bigger picture	0.649	0.400	0.345	0.343	0.485	0.434	**0.936**	0.326	0.505
Media multitasking gives me different points of view	0.633	0.365	0.241	0.368	0.443	0.452	**0.927**	0.364	0.530
multitask with media so that I can gain knowledge	0.569	0.397	0.318	0.342	0.482	0.453	**0.886**	0.375	0.448

Multi-media channel preference [8]									
I like switching back and forth between different media	0.456	0.462	0.350	0.606	0.344	0.633	0.321	**0.834**	0.451
I like to juggle between media	0.479	0.428	0.482	0.563	0.331	0.671	0.334	**0.911**	0.505
I like to do more than one media activity at a time	0.475	0.415	0.460	0.543	0.273	0.640	0.401	**0.894**	0.468
I like having multiple streams of media stimulation	0.430	0.462	0.458	0.557	0.352	0.66	0.364	**0.914**	0.527
Social benefits [9]									
Multitasking with media gives me a sense of belonging	0.460	0.311	0.404	0.369	0.345	0.599	0.482	0.503	**0.941**
Media multitasking helps me feel available for my friends and family	0.452	0.349	0.403	0.364	0.416	0.585	0.532	0.520	**0.946**
When I multitask with media, I feel closer to other people	0.404	0.316	0.377	0.344	0.390	0.577	0.471	0.504	**0.912**
Media multitasking helps me to feel connected with my friends and family	0.441	0.329	0.449	0.318	0.379	0.645	0.511	0.510	**0.897**

Note: * Item removed during scale purification. All factor loadings are significant at $p < .001$

Appendix 2: Reliability and validity indexes

	AVE	ρ_c	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
[1] Assimilation	0.797	0.940	***0.893***	0.453	0.418	0.535	0.477	0.659	0.766	0.573	0.525
[2] Comfort	0.773	0.931	0.415	***0.879***	0.417	0.756	0.610	0.566	0.521	0.547	0.382
[3] Compulsive	0.894	0.962	0.389	0.390	***0.945***	0.391	0.291	0.580	0.369	0.530	0.467
[4] Convenience	0.763	0.928	0.491	0.673	0.362	***0.873***	0.457	0.613	0.475	0.701	0.406
[5] Effectiveness	0.879	0.967	0.451	0.564	0.28	0.418	***0.938***	0.507	0.582	0.393	0.432
[6] Gratification	0.715	0.909	0.590	0.502	0.526	0.538	0.465	***0.846***	0.583	0.828	0.721
[7] Information	0.768	0.929	0.696	0.442	0.335	0.401	0.526	0.499	***0.876***	0.462	0.576
[8] MMC preference	0.790	0.938	0.528	0.495	0.497	0.634	0.365	0.732	0.398	***0.889***	0.592
[9] Social	0.854	0.959	0.485	0.353	0.442	0.378	0.413	0.65	0.541	0.551	**0.924**
Innovativeness	.888	.666									
Sensation seeking	.808	.944									

Note: Diagonal bold and italicized are square roots of AVE. Below the diagonal elements are bivariate correlations while above the diagonal elements are the HTMT values

Appendix 3:

Invariance testing using permutation – segment 1 vs segment 2

Dimensions of the P-MMU	Compositional invariance		Equality of composite mean values		Equality of variances	
	Correlation	CI	Difference	CI	Difference	CI
Assimilation	.999	[.997, 1]*	-.142	[-.268, .245]*	.477	[-.416, .436]
Comfort with MM	.995	[.988, 1]*	.085	[-.252, .262]*	-.066	[-.295, .318]*
Compulsive addictive	.999	[.998, 1]*	-.120	[-.255, .238]*	.095	[-.310, .332]*
Convenience	.996	[.955, 1]*	.135	[-.259, .258]*	.133	[-.329, .388]*
Effectiveness and efficiency	.998	[.996, 1]*	-.010	[-.248, .257]*	.422	[-.338, .382]
Emotional gratification	.922	[.989, 1]	-.156	[-.260, .240]*	.043	[-.298, .326]*
Information and knowledge	.998	[.982, 1]*	.119	[-.258, .254]*	.048	[-.366, .370]*
Multi-media channel preference	.994	[.987, 1]*	-.031	[-.251, .262]*	.282	[-.346, .348]*
Social benefits	.999	[.998, 1]*	-.236	[-.272, .259]*	.351	[-.303, .298]

Note: Applying all three segments to the same model confirms configular invariance. CI = confidence interval. * denotes that invariance is confirmed, i.e. values within their respective CIs.