Title: Using Big Data as a Window into Consumers' Psychology

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Abstract:

The rise of "Big Data" had a big impact on marketing research and practice. In this article, we first highlight sources of useful consumer information that are now available at large scale and very little or no cost. We subsequently discuss how this information - with the help of new analytical techniques - can be translated into valuable insights on consumers' psychological states and traits that can, in turn, be used to inform marketing strategy. Finally, we discuss opportunities and challenges related to the use of Big Data as a window into consumers' psychology, and provide recommendations for how to implement related technologies in a way that benefits both businesses and consumers.

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The availability of data at large volume, variety, velocity and veracity, often termed as "Big Data", had a big impact on marketing research [1] and practice [2]. The wealth of personal information available about consumers online makes it possible to understand and cater to the individual needs of consumers better than ever before. Whether it is their Spotify playlists, Facebook profile, Google search queries, or mobile location, the digital footprints consumers leave with every step they take in the digital environment create extensive records of their personal habits and preferences. By tapping into this rich pool of consumer data, businesses can enhance consumers' experience by better matching the marketing offering to consumers' preferences and do so at the appropriate moment.

Applications of Big Data in marketing have largely focused on (a) assessing customers' preferences [e.g., 3], (b) predicting what customers are most likely to buy next [e.g., 4–6], (c) improving targeted advertising [e.g., 7,8], (d) understanding brand perceptions [e.g., 9,10], and (e) describing the competitive landscape [e.g., 11]. See Wedel and Kannan (2016) for a review. However, investigations of how Big Data can help inform some of the more psychological aspects of consumer behavior that is aimed at understanding - rather than merely predicting - consumer attitudes and emotions has thus far only received scant attention. Davenport, Harris & Kohli (2001, p. 63) note that holding vast amounts of customer data might help businesses to "know more about their customers" but does not necessarily allow them to "know the customers themselves". The focus of this paper is to highlight the existing work and discuss the potential of using Big Data as a means to better understand consumers' stable psychological traits as well as more malleable psychological states.

New sources of consumer information

Traditional approaches to gathering "human-centric" consumer information include extensive customer surveys, focus groups, interviews, observation studies and limited scope secondary data such as scanner panel data [1]. For example, as part of the Nordstrom's Personal Touch program, personal shoppers recorded detailed information on customers likes and dislikes, their lifestyle and tastes through telephone and face-to-face conversations as well as observations made in the store [12]. While the outlined approaches can generate valuable customer knowledge, they are not only expensive and time-consuming - and therefore difficult to scale - but also prone to numerous well established response biases [13]. For example, even the most motivated customer will find it difficult to accurately recall the purchases they made over the past four weeks or the exact feeling they experienced when purchasing a specific product.

Thanks to technological advances in the collection, storage and analysis of large amounts of data, businesses can now gain valid insights on millions of consumers by looking at the digital records that are passively collected as consumers go about their daily lives. In fact, observing the behavior of a consumer in a traditional retail store is very similar to analyzing the journey of a customer who is browsing a company's online store (e.g., one can examine the characteristics of products the user has looked at and/or bought, measure the time they took to make a decision, or implement mouse-tracking technologies to study the decision process). Similarly, customer forums, product reviews and posts in social media make it possible to observe large and natural "focus groups" at very little to no cost [11].

The sources of information businesses can tap into to learn more about their consumers are almost limitless, and it would go beyond the scope of this paper to discuss all of them in detail (for an overview see Wedel and Kannan 2016, Figure 2). Among the most vital ones are historical purchasing data, credit card records, search queries, browsing histories, blog posts, social media profiles, and smartphone sensor data (e.g., GPS location). Importantly, it is often possible to combine the information extracted from different sources to form a more holistic picture of a consumer's daily habits and preferences. By integrating information obtained from a consumer's social media profile, their phone logs and sensor data as well as their credit card spending, for example, one can get a fairly accurate picture of *what* a consumer has done *when* and with *whom*.

These new sources of data not only come from various sources, but they also come in multiple formats. While traditional data have been primarily structured in a numeric format, social media data, are primarily unstructured including, text, images, audio and video. Accordingly, different analytical approaches are needed to convert such data into knowledge and insights.

Turning Big Data into human-centric customer knowledge

The task of turning vast amounts of - often unstructured – data into insightful consumer knowledge is not easy and often requires the application of analytical techniques that are outside of the standard methodological tool box of consumer behavior researchers [14]. However, recent years have seen the rise of so-called computational social science research, a discipline aimed at applying methodologies from the computer sciences to questions asked by social scientists [15]. While the range of possible applications of such methodologies to social science questions is bounded only by the creativity and imagination of the researcher, here we focus on two types of insights that have recently attracted a considerable amount of attention among researchers and practitioners alike: the prediction of (1) relatively stable *psychological traits* that help explain consumers' general tendency to think, feel and behave in a certain way, and (2) malleable *psychological states* that express consumers' attitudes and emotions in-the-moment and help to put their behavior in context.

Predicting consumers' psychological traits

The investigation of stable psychological traits such as personality, regulatory focus, or need for cognition, has a long-standing tradition in consumer behavior research [16]. One of the most consistent findings suggests that consumers show more positive cognitive, emotional and behavioral responses to products, brands or marketing messages that match their own psychological traits [e.g., 17–20]. For example, an extroverted and open-minded consumer might experience more positive emotions and report a higher intention towards a retail brand that specializes in flashy and unusual clothes, or that uses extroverted and creative language to advertise their products (e.g., "Stand out from the crowd and feel unique with our latest spring collection"). Businesses have long used such insights for branding and advertising purposes [e.g., 21].

However, because unlike demographics and past purchases, latent psychological traits cannot be observed directly, the opportunities to target consumers and personalize advertising based on psychological traits have been limited. If a mobile phone provider, for instance, decided to create a strong extroverted brand, it was very difficult to focus its advertising efforts on extroverted consumers short of choosing media channels (e.g., TV shows) that are predicted based on questionnaires or managerial judgement to have a larger proportion of extroverts. Instead, the branded marketing message had been primarily focused on mass marketing, broadcasting to large and heterogeneous audiences, thereby limiting its effectiveness.

In the age of Big Data, however, psychological traits – including personality, IQ and political orientation – can be accurately predicted from consumers' digital footprints. Researchers have demonstrated the ability to accurately infer personal traits from (a) personal websites [22], (b) Facebook or Twitter profiles [23–25], (c) blogs [26], and (d) language use [27–30]. This digital form of psychometric assessment promises to be a game changer in the application and empirical evaluation of psychographic marketing. In an early pioneering study, for example, Hauser and colleagues inferred cognitive styles (e.g., analytic vs. emotional) from clickstream data and showed that matching a website's "look and feel" to consumers' dominant motivational orientation can increase sales by up to 20% [7]. Similarly, Matz and colleagues showed that inferring the personality of Facebook users from their Likes, and matching the content of real advertising campaigns (products and marketing messages) to their dominant personality traits can significantly increase click-through and conversion rates [31]. As the digital assessment of psychological traits becomes more widespread and readily available (e.g., LIWC for computerized text analysis; ApplyMagicSauce and StatSocial for personality predictions), consumer behavior scholars will be able to build on this early research and test the effectiveness of psychographic targeting in different domains (e.g., retail, charitable giving, political campaigning) and channels (e.g., social media, email, in-store), using different psychological traits (e.g., personality, cognitive style, motivational orientations), and different outcome measures (e.g. clicks, purchases, long-term retention).

Turning customer data into meaningful psychological profiles offers tremendous opportunities for a more holistic Customer Relations Management [CRM; ,32] that bridges the gap between online and offline channels. For example, knowing that a consumer follows a cognitive style that is analytical rather than emotional, makes it possible for both computers online and salespeople in brick and mortar stores to adapt their communication to the preferences of the customer.

Predicting consumers' psychological states

As we have outlined, psychological traits play an important role in understanding and predicting consumer behavior. However, marketing researchers have long recognized that they cannot account for the full variation in consumer behavior [33]. This is, because psychological traits do not operate in a vacuum, but instead are expressed in a certain context, these traits are often influenced by situational factors [34, 35]. For example, consumers who are in a positive mood use more heuristic - rather than systematic - information processing and evaluate products and brands more favorably [for an overview on the effect of mood on consumer behaviour see 36]. Hence marketers can benefit from paying close attention to and capitalize on customers' psychological states.

However, because of the transient nature of psychological states identifying such states in real time is even more challenging than identifying psychological traits. Similar to psychological traits, psychological states have traditionally been tied to questionnaire measures [e.g., the PANAS scale for positive and negative affect; 37]. However, these have been mainly performed for academic purposes as the ability of firms to measure and act in real time on varying psychological states using surveys is largely impractical. Fortunately, new data sources and advances of analytics techniques make psychological traits predictable from a broad variety of digital footprints collected in real time [see e.g., 38, 39]. Consumers' mood and emotions have been successfully predicted from spoken and written language [40], video [41], wearable devices [42], smartphone sensor data [43], and even information obtained from the environment such as weather or physical location [44].

While marketers have long used retrospective analyses of consumer sentiment in the study of online word-of-mouth [45, 46], the ability to assess consumers' psychological states and sentiment in real time provides consumer behavior researchers and practitioners with tremendous opportunities to personalize marketing content to the immediate psychological needs of consumers. Context-aware recommendation systems, for example, can use information on consumers' mood or emotions to increase the relevance of the content that is suggested to the user [47]. Such context-aware recommenders, that take into account consumers' emotions, have shown improved recommendations for music [48], movies [49, 50], and images [51].

Combining Psychological Traits and States

The combination of psychological traits (variability across consumers) and psychological states (variability within consumers over time) offers an unprecedented understanding of consumers' unique needs as they relate to the situation-specific expressions of more stable motivations and preferences [33; also compare to the theory of free traits, 52]. For example, extroverted consumers might be more likely to respond to personality-matched advertisements [e.g., 19] when they are in an extroverted situation that highlights and reinforces their extroverted innate nature or when they find themselves in an introverted situation that lacks the excitement and stimulation they need to thrive. The availability of data and analysis tools to investigate personality traits and states in real time, provide a fruitful avenue to exploring the interesting interactions between personality traits and states and how consumers may react to offer that leverage such interactions.

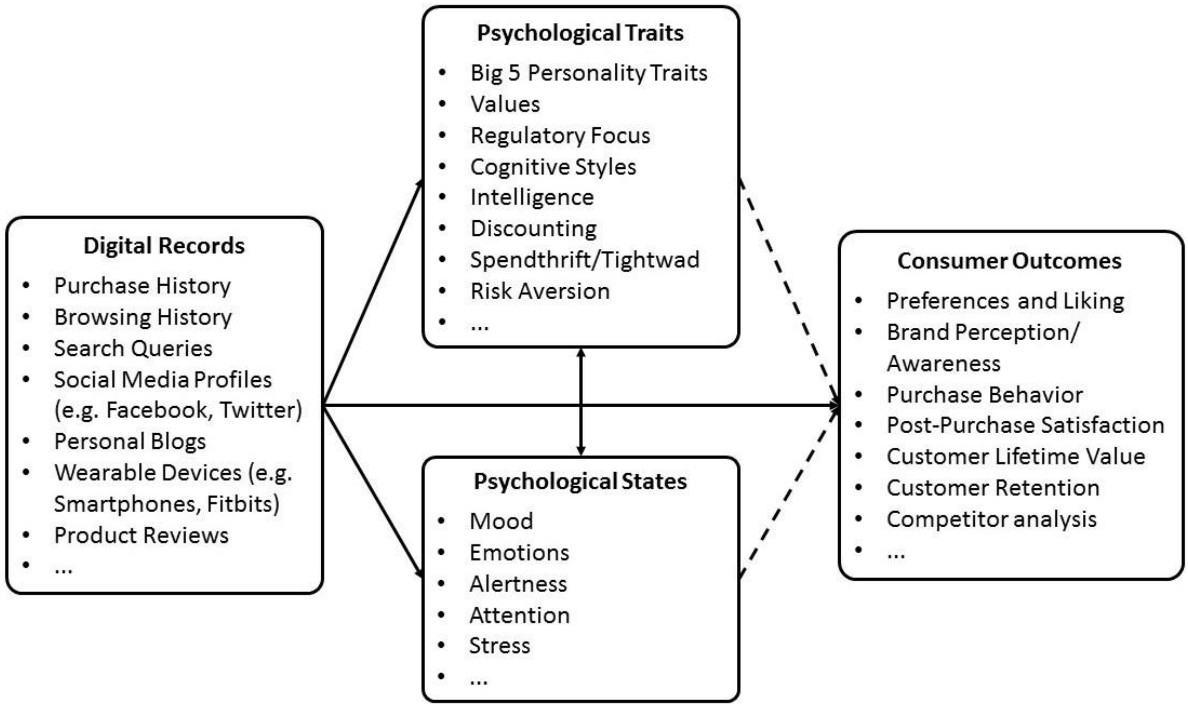

Figure 1. Leveraging Big Data to Infer Psychological Traits and States and Affect Customer Behavior.

Figure 1 summarizes the outlined opportunities of using Big Data in the context of consumer research. As we have discussed throughout the paper, the wealth of personal consumer information available at little to no cost makes it possible to not only predict consumer outcomes, but to also understand consumers' psychological needs and motivations at both the state and trait levels. Understanding consumers' psychological states and traits can then be used to better match the firm's marketing offerings to customers' needs and preferences, and hence improve business and consumer outcomes.

Opportunities and Challenges

The combination of information about 'what one does' with deeper understanding of 'who one is' offers tremendous opportunities to not only boost the effectiveness of marketing campaigns but also to help consumers make better decisions. The pre-selection of content that is in line with consumers' psychological needs can alleviate the problem of choice overload [53, 54] and help consumers to maximize the satisfaction and happiness they gain from their choices [55]. In addition, psychologically-customized health messages are known to be effective in changing behaviors among patients and groups who are at risk [56, 57]. Targeting highly neurotic individuals who display early signs of depressions with ads that guide them to self-help pages or offer professional advice, for example, could have a tremendous positive impact on the well-being of some of the more vulnerable members of society, and even save lives.

Alongside the benefits psychologically-personalized marketing provides, it also raises new ethical challenges. While psychological targeting can help consumers make better choices, it could also be used in a way that exploits “weaknesses” in a person’s character. For example, one could target individuals who are prone to compulsive or addictive behavior [58] with ads for an online casino, or exclude them from receiving insurance ads. In fact, Facebook was recently criticized for analyzing teenagers’ emotional or mental state using their Facebook profiles. While Facebook said it does not currently use such inferences for targeting, even the collection of such data raised consumers’ ethical concerns. This more critical side of increasingly personalized marketing is reflected in general public skepticism [59,60]. A 2010 survey of American Internet users showed that less than 20% expressed a preference for targeted ad, while 64% viewed personalized advertising as “intrusive” [59]. In 2012, this skepticism reached a public peak in response to a “scandal” involving the U.S. retail giant Target. Using data-driven recommendation algorithms, Target had promoted baby equipment to a pregnant teenage girl in Minnesota, whose parents had previously been unaware of the pregnancy. With the introduction of even more sophisticated prediction algorithms that not only analyze individual behaviors but make inferences about a consumers’ intimate psychological traits and states, these concerns are unlikely to change for the better. We therefore suggest to use the knowledge of consumers’ psychological traits to provide optional services that consumers can actively opt-in to. Given that privacy concerns are known to negatively impact the effectiveness of personalized advertising [61], while giving consumers more control over their personal information positively affects their willingness to click on personalized ads [62], such an approach is not only in the interest of consumers but eventually in the best self-interest of businesses. By implementing psychologically-personalized targeting in a transparent way that gives data ownership and control to consumers, businesses can avoid the risk of reputational damage and instead turn psychological customization into a desirable component of their value proposition to customers.

Conclusion

Taken together, the ability to predict consumers' psychological traits and states from their digital footprints offers exciting new opportunities for digital marketing. We expect both researchers and practitioners to go beyond the understanding and prediction of psychological states and traits and towards real-time "optimization" of marketing actions on the basis of these predictions. Much like in the scene in the science fiction movie Minority Report, where advertising billboards are personalized to the emotional state of the person walking past them, businesses will be able to optimize the advertising a consumer is exposed to in real-time and at a level of detail never before possible. For example, one could use information about a person's momentary heart rate extracted through their headphones to determine which song to play next, extract emotions from a person's facial expression to change the color scheme of a website, or recommend the next tourist attraction in a new city as a function of the person's predicted personality and their current level of physical activity. We encourage researchers to continue to explore these exciting opportunities.

1. **Wedel M, Kannan PK: **Marketing analytics for data-rich environments**. *J. Mark.* 2016, **80**:97–121.
2. **van den Driest F, Sthanunathan S, Weed K: **Building an insights engine**. *Harv. Bus. Rev.* 2016, **94**:15.
3. Jacobs BJD, Donkers B, Fok D: **Model-based purchase predictions for large assortments**. *Mark. Sci.* 2016, **35**:389–404.
4. Ghose A, Ipeirotis PG, Li B: **Designing ranking systems for hotels on travel search engines by mining user-generated and crowdsourced content**. *Mark. Sci.* 2012, **31**:493–520.
5. Lu S, Xiao L, Ding M: **A video-based automated recommender (VAR) system for garments**. *Mark. Sci.* 2016, **35**:484–510.
6. Linden G, Smith B, York J: **Amazon.com recommendations: Item-to-item collaborative filtering.** *IEEE Comput. Soc.* 2003, **7**:76–80.
7. **Hauser JR, Urban GL, Liberali G, Braun M: **Website Morphing**. *Mark. Sci.* 2009, **28**:202–223.
8. Trusov M, Ma L, Jamal Z: **Crumbs of the cookie: User profiling in customer-base analysis and behavioral targeting**. *Mark. Sci.* 2016, **35**:405–426.
9. Culotta A, Cutler J: **Mining brand perceptions from twitter social networks**. *Mark. Sci.* 2016, **35**:343–362.
10. Tirunillai S, Tellis GJ: **Mining marketing meaning from online chatter: Strategic brand analysis of big data using latent dirichlet allocation**. *J. Mark. Res.* 2014, **51**:463–479.
11. Netzer O, Feldman R, Goldenberg J, Fresko M: **Mine your own business: Market-structure surveillance through text mining**. *Mark. Sci.* 2012, **31**:521–543.
12. Davenport TH, Harris JG, Kohli AK: **How do they know their customers so well?** *MIT Sloan Manag. Rev.* 2001, **42**:63.
13. Podsakoff PM, Organ DW: **Self-reports in organizational research: Problems and prospects**. *J. Manage.* 1986, **12**:531–544.
14. Kosinski M, Matz SC, Gosling SD, Popov V, Stillwell D: **Facebook as a research tool for the social sciences**. *Am. Psychol.* 2015, **70**:543–556.
15. Lazer D, Pentland AS, Adamic L, Aral S, Barabasi AL, Brewer D, Christakis N, Contractor N, Fowler J, Gutmann M: **Life in the network: the coming age of computational social science**. *Sci. (New York, NY)* 2009, **323**:721.

16. Kotler P, Armstrong G: *Principles of marketing*. pearson education; 2010.
17. Aaker JL: **The malleable self : The role of self expression in persuasion**. *J. Mark. Res.* 1999, **36**:45–57.
18. Sirgy MJ: **Using self-congruity and ideal congruity to predict purchase motivation**. *J. Bus. Res.* 1985, **13**:195–206.
19. Hirsh JB, Kang SK, Bodenhausen G V: **Personalized persuasion: tailoring persuasive appeals to recipients' personality traits**. *Psychol. Sci.* 2012, **23**:578–581.
20. Wheeler SC, Petty RE, Bizer GY: **Self-schema matching and attitude change: Situational and dispositional determinants of message elaboration**. *J. Consum. Res.* 2005, **31**:787–797.
21. Aaker JL: **Dimensions of brand personality**. *J. Mark. Res.* 1997, **34**:347–356.
22. Marcus B, Machilek F, Schütz A: **Personality in cyberspace: personal Web sites as media for personality expressions and impressions.** *J. Pers. Soc. Psychol.* 2006, **90**:1014–1031.
23. Quercia D, Kosinski M, Stillwell D, Crowcroft J: **Our Twitter profiles, our selves: Predicting personality with Twitter**. In *IEEE International Conference on Social Computing*. 2011:180–185.
24. **Kosinski M, Stillwell D, Graepel T: **Private traits and attributes are predictable from digital records of human behavior**. *Proc. Natl. Acad. Sci.* 2013, **110**:5802–5.
25. Youyou W, Kosinski M, Stillwell D: **Computer-based personality judgments are more accurate than those made by humans**. *Proc. Natl. Acad. Sci.* 2014, **112**:1036-1040.
26. Yarkoni T: **Personality in 100,000 words: A large-scale analysis of personality and word use among bloggers**. *J. Res. Pers.* 2010, **44**:363–373.
27. *Netzer O, Lemaire A, Hertzenstien M: **When words sweat: Identifying signals for loan default in the text of loan applications.** Working Paper.
28. **Park G, Schwartz H, Eichstaedt J, Kern ML, Kosinski M, Stillwell D, Ungar LH, Seligman MEP: **Automatic personality assessment through social media language**. *J. Pers. Soc. Psychol.* 2014, **108**:934–952.
29. Schwartz HA, Eichstaedt JC, Kern ML, Dziurzynski L, Ramones SM, Agrawal M, Shah A, Kosinski M, Stillwell D, Seligman MEP, et al.: **Personality, gender, and Age in the language of social media: The open-vocabulary approach**. *PLoS One* 2013, **8**:e73791.
30. Pennebaker JW, King LA: **Linguistic styles: language use as an individual**

difference. *J. Pers. Soc. Psychol.* 1999, **77**:1296.

31. **Matz S, Kosinski M, Nave G, Stillwell D: **Personality-matching increases the effectiveness of digital advertising.** Working Paper.
32. Odekerken-Schröder G, De Wulf K, Schumacher P: **Strengthening outcomes of retailer–consumer relationships: The dual impact of relationship marketing tactics and consumer personality**. *J. Bus. Res.* 2003, **56**:177–190.
33. Belk RW: **Situational variables and consumer behavior**. *J. Consum. Res.* 1975, **2**:157–164.
34. Kenrick DT, Funder DC: **Profiting from controversy: Lessons from the person-situation debate.** *Am. Psychol.* 1988, **43**:23.
35. Fleeson W, Noftle E: **The end of the person–situation debate: An emerging synthesis in the answer to the consistency question**. *Soc. Personal. Psychol. Compass* 2008, **2**:1667–1684.
36. Bagozzi RP, Gopinath M, Nyer PU: **The role of emotions in marketing**. *J. Acad. Mark. Sci.* 1999, **27**:184–206.
37. Watson D, Clark L a, Tellegen a: **Development and validation of brief measures of positive and negative affect: the PANAS scales.** *J. Pers. Soc. Psychol.* 1988, **54**:1063–1070.
38. Zeng Z, Pantic M, Roisman GI, Huang TS: **A survey of affect recognition methods: Audio, visual, and spontaneous expressions**. *IEEE Trans. Pattern Anal. Mach. Intell.* 2009, **31**:39–58.
39. *D'mello SK, Kory J: **A review and meta-analysis of multimodal affect detection systems**. *ACM Comput. Surv.* 2015, **47**:43.
40. Cowie R, Douglas-Cowie E, Savvidou* S, McMahon E, Sawey M, Schröder M: **"FEELTRACE": An instrument for recording perceived emotion in real time**. In *ISCA tutorial and research workshop (ITRW) on speech and emotion*. 2000.
41. Teixeira T, Wedel M, Pieters R: **Emotion-induced engagement in internet video advertisements**. *J. Mark. Res.* 2012, **49**:144–159.
42. AlHanai T, Ghassemi MM: **Predicting latent narrative mood using audio and physiologic data**. In *AAAI*. 2017.
43. **LiKamWa R, Liu Y, Lane ND, Zhong L: **Moodscope: Building a mood sensor from smartphone usage patterns**. In *Proceeding of the 11th annual international conference on Mobile systems, applications, and services*. ACM; 2013:389–402.
44. Park H-S, Yoo J-O, Cho S-B: **A context-aware music recommendation system using**

fuzzy bayesian networks with utility theory. In *International Conference on Fuzzy Systems and Knowledge Discovery*. Springer; 2006:970–979.

45. Das SR, Chen MY: **Yahoo! for Amazon: Sentiment extraction from small talk on the web**. *Manage. Sci.* 2007, **53**:1375–1388.
46. Jansen BJ, Zhang M, Sobel K, Chowdury A: **Twitter power: Tweets as electronic word of mouth**. *J. Am. Soc. Inf. Sci. Technol.* 2009, **60**:2169–2188.
47. Zheng Y, Mobasher B, Burke R: **Emotions in context-aware recommender systems**. In *Emotions and Personality in Personalized Services*. Springer; 2016:311–326.
48. Lee JS, Lee JC: **Music for my mood: A music recommendation system based on context reasoning**. In *European Conference on Smart Sensing and Context*. Springer; 2006:190–203.
49. Winoto P, Tang TY: **The role of user mood in movie recommendations**. *Expert Syst. Appl.* 2010, **37**:6086–6092.
50. Shi Y, Larson M, Hanjalic A: **Mining mood-specific movie similarity with matrix factorization for context-aware recommendation**. In *Proceedings of the workshop on context-aware movie recommendation*. ACM; 2010:34–40.
51. Tkalčič M, Burnik U, Košir A: **Using affective parameters in a content-based recommender system for images**. *User Model. User-adapt. Interact.* 2010, **20**:279–311.
52. Little BR: **Free traits, personal projects and idio-tapes: Three tiers for personality psychology.** Psychol. Inq. 1996, 7:340–344.
53. Iyengar SS, Lepper MR: **When choice is demotivating: can one desire too much of a good thing?** *J. Pers. Soc. Psychol.* 2000, **79**:995–1006.
54. Schwartz B, Ward A: **Doing better but feeling worse: The paradox of choice**. In *Positive psychology in practice*. Edited by Linley AP, Joseph S. John Wiley & Sons, Inc; 2004:86–104.
55. Matz S, Gladstone J, Stillwell D: **Money buys happiness when spending fits our personality**. *Psychol. Sci.* 2016, **27**:715–725.
56. Noar SM, Benac CN, Harris MS: **Does tailoring matter? Meta-analytic review of tailored print health behavior change interventions**. *Psychol. Bull.* 2007, **133**:673–693.
57. Mann T, Sherman D, Updegraff J: **Dispositional motivations and message framing: a test of the congruency hypothesis in college students.** *Heal. Psychol.* 2004, **23**:330.
58. Bagby RM, Vachon DD, Bulmash EL, Toneatto T, Quilty LC, Costa PT: **Pathological**

gambling and the five-factor model of personality. *Pers. Individ. Dif.* 2007, **43**:873–880.

59. McDonald AM, Cranor LF: **Americans' attitudes about internet behavioral advertising practices**. In *Proceedings of the 9th annual ACM workshop on privacy in the electronic society*. ACM; 2010:63–72.
60. Ur B, Leon PG, Cranor LF, Shay R, Wang Y: **Smart, useful, scary, creepy: perceptions of online behavioral advertising**. In *proceedings of the eighth symposium on usable privacy and security*. ACM; 2012:4.
61. Goldfarb A, Tucker CE: **Privacy regulation and online advertising**. *Manage. Sci.* 2011, **57**:57–71.
62. *Tucker CE: **Social networks, personalized advertising, and privacy controls**. *J. Mark. Res.* 2014, **51**:546–562.

Annotated Citations

1	Wedel & Kannan (2016)	Wedel and Kannan (2016) offer a critical review of marketing analytics methods. Examining different types of data (e.g. structured vs. unstructured, firm internal vs. external), they review the potential of these methods and subsequently highlight current and future directions for new analytical tools with regard to (a) optimized marketing-mix spending, (b) personalization, and (c) data security.
2	van den Driest, Sthanunathan & Weed (2016)	Van den Driest et al. (2016) provide a practitioner-oriented discussion on how to successfully implement customer-centricity as a powerful source of competitive advantage. Focusing on the retail giant Unilever, they outline operational and people characteristics that facilitate the development and application of highly functional "insight engines" on the basis of Big Data.
7	Hauser, Urban, Liberali & Braun (2009)	Hauser et al. (2009) demonstrate the value of dynamic website morphing in a large-scale experiment using data from 835 BT Group (former British Telecom) customers. They infer cognitive styles (e.g. analytic vs. emotional) from clickstream data and show that matching a website's "look and feel" to consumers' dominant motivational orientation can increase sales by up to 20%.
24	Kosinski, Stillwell & Graepel (2013)	Kosinski et al (2013) demonstrate the validity of preference-based personality assessment via social media. Using data of more than 58 thousand Facebook users, they show that highly intimate demographic and socio-psychological characteristics (e.g. political orientation, IQ or personality) can be accurately predicted from people's Facebook Likes.
27	Netzer, Lemaire & Hertzenstien (working paper)	Netzer et al. use text-mining and machine-learning tools to automatically process and analyze the raw text in thousands of loan requests from an online crowdfunding platform. They find that borrowers, consciously or not, leave traces of their intentions, circumstances, and personality traits in the text they write when applying for a loan.
28	Park, Schwartz, Eichstaedt, Kern, Kosinski, Stillwell, Ungar & Seligman (2014)	Park et al. (2014) demonstrate the validity of language-based personality assessment via social media. Using an open-vocabulary analysis of the status updates of more than 70 thousand Facebook users, they show that language-based predictions of personality (a) converge with self and other reports, (b) accurately discriminate between traits (c) are stable over time and (d) exhibit

		correlations with external criteria (e.g. life satisfaction) similar to those found for self-reports.
31	Matz, Kosinski, Nave & Stillwell (working paper)	Matz et al. demonstrate the effectiveness of personality-based targeting in several large-scale experiments on Facebook. They show that inferring the personality of Facebook users from their Likes, and matching the content of real advertising campaigns (products and marketing messages) to their dominant personality traits can significantly increase click-through and conversion rates
39	D'mello & Kory (2015)	D'mello and Kory (2015) provide a systematic review of multimodal affect detection systems. Based on a quantitative review and meta-analysis of 90 peer-reviewed affect detection systems, they show that (a) the majority of systems relies on person-dependent models, fusing audio and visual, (b) multimodal systems were consistently better than unimodal systems, and (c) systems were substantially less accurate for natural than for acted emotional reactions.
43	LiKamWa, Liu, Lane & Zhong (2013)	LiKamWa et al. (2013) demonstrate the validity of assessing people's mood on the basis of their smartphone sensor data. Using smartphone logged data of 32 participants collected over a period of two months, they show that people's daily mood can be accurately predicted from their communication history and patterns of application usage.
61	Tucker (2014)	Tucker (2014) investigates how consumers' perceived control over privacy affects their willingness to engage with personalized advertising. Using data from a randomized field experiment, she demonstrates that giving people more control over their personally identifiable information increases – rather than decreases – the likelihood of them clicking on personalized ads.