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# Data Mining Approach for Examining Personality, Cognitive, and Emotional Features of Social Network Consumers

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## Abstract

The current research examines the personality characteristics and emotional intelligence of young adult consumers who shop through social media. Consumer behaviour has long piqued the research community's curiosity. Contemporary customer behavior analysis considers a wide variety of influences affecting the consumer and recognizes a wide variety of buying behaviors other than shopping. Due to the fact that online sales are now an everyday occurrence, it is beneficial to research online customers who are social media users who shop via social media. Personality traits and emotional characteristics, as described in emotional intelligence, are two critical components that affect consumer behaviour. Emotional intelligence is a component of personality and intellectual ability that is inherited by one's parents and grows - develops over one's lifespan. The term "personality" refers to the pattern of emotions, feelings, and actions that distinguishes individuals from one another. These have an effect on how an individual thinks, feels, and behave against itself and others. The results were gathered by having participants complete the self-report questionnaire Trait Emotional Intelligence (TEIQue) for emotional intelligence and Eysenck Personality Questionnaire (EPQ) for personality characteristics associated with personality disorders. The collected data were then chosen for review, undergoing necessary transformations to ensure that they were in a format appropriate for implementation of the respective machine learning algorithms provided in the R Software. Additionally, the appropriate set of algorithm parameters was calculated based on the implementation scenario in order to generate inference rules. Several algorithms were introduced in response to particular research concerns, including classification algorithms for the generation of decision trees based on the four more general factors of emotional intelligence (welfare, selfcontrol, emotionality, and sociability), as well as personality characteristics of social network users. Following a weighting and criterion-based analysis, the findings obtained present consumers' ratings, which are used to determine the degree of emotional intelligence and personality traits. Personality and emotional intelligence indices may be critical in elucidating social network users' consumer behaviour.

## Keywords

Consumer Behaviour, Emotional Intelligence, Personality, Data Mining

## 1. INTRODUCTION

The explosive growth of social networks has created a wealth of data, providing a unique opportunity to study and understand human behavior. This review paper explores the application of data mining techniques to analyze the personality, cognitive, and emotional features of social network consumers (Hevner et al., 2004). We examine the evolution of this field, the various data sources, and the state-of-the-art methodologies used for mining and analyzing user characteristics on social media platforms. Furthermore, we discuss the potential applications and ethical considerations associated with this research area (Blachnio et al., 2013).

The advent of social networking platforms has revolutionized the way people interact, share information, and express themselves online. These platforms generate massive volumes of data daily, which offer insights into the personalities, cognitive processes, and emotional states of their users. Data mining techniques have become instrumental in uncovering patterns and trends within this data, thereby enabling researchers to gain valuable insights into social network consumers' behaviors (Blachnio et al., 2013; Hevner et al., 2004).

In the 21st century, the proliferation of social networking platforms has redefined the way people communicate, interact, and share their lives in the digital realm. The magnitude of this transformation is mirrored by the colossal volume of data generated daily within the confines of these virtual social spaces. This explosion of user-generated content on platforms such as Facebook, Twitter, Instagram, and TikTok has given rise to an exciting frontier in the world of data science: the analysis of personality, cognitive processes, and emotional states of social network consumers (Blachnio et al., 2013).

This review paper embarks on an exploration of this rapidly evolving research domain, shedding light on the intricacies of data mining techniques applied to unveil the profound aspects of human behavior within the digital landscape. The data extracted from social networks not only encapsulate the visible facets of online life but also serve as a treasure trove of insights into the inner workings of the human mind and heart. The ability to decode this rich tapestry of information has profound implications for various fields, including psychology, marketing, and even public health (Blachnio et al., 2013).

The fundamental premise underlying this research endeavor is that social networks offer a unique platform for individuals to express themselves. These expressions are not limited to mere words; they encompass a broad spectrum of communication modalities, ranging from text-based status updates and comments to multimedia content such as images, videos, and audio. Furthermore, the interactions between users, manifesting as likes, shares, comments, and private messages, offer windows into the cognitive and emotional responses of individuals, as they react to the content they encounter. User profiles on social media platforms themselves often contain invaluable demographic data, which, when mined, can provide insights into the correlation between user characteristics and online behavior (Hevner et al., 2004).

The transformative capabilities of data mining techniques are harnessed to dissect this vast repository of information. The objective is to discern patterns and trends that underlie the expression of personality, the operation of cognitive processes, and the display of emotional states within the digital universe. It's no longer limited to understanding what people say, but also how they say it, what they share, and how they react to the content they consume.

This multidimensional analysis of users in the social network ecosystem can be compartmentalized into several key areas:

- **Sentiment Analysis:** Textual content is subjected to sentiment analysis, wherein algorithms categorize it as positive, negative, or neutral. This provides insights into the emotional tone and sentiment of user-generated content.
- **Personality Trait Analysis:** The Big Five personality model, comprising Openness, Conscientiousness, Extroversion, Agreeableness, and Neuroticism, can be inferred from textual content, providing valuable insights into user personalities.
- **Emotion Detection:** Algorithms analyze image and video data, uncovering facial expressions and body language to determine emotional states. These emotions can include happiness, sadness, anger, surprise, and more.
- **Social Network Analysis:** This facet of data mining involves dissecting the relationships, communities, and influential nodes within the social network. It goes beyond individual characteristics to explore the collective behavior within the network (Hevner et al., 2004).

The applications stemming from this multifaceted analysis are broad and impactful. From personalized content recommendations based on user characteristics to highly-targeted advertising campaigns that align with the cognitive and emotional states of users, the implications for various industries, including marketing, mental health, and education, are immense. Additionally, the data-driven early detection of individuals at risk of mental health issues is an area with tremendous potential, allowing for timely intervention and support.

However, as the power of data mining in the context of social networks continues to expand, it is imperative to address the ethical considerations that accompany this field. Issues such as user privacy, consent, and the responsible use of personal data are pivotal to ensuring the ethical progression of this research area (Hevner et al., 2004).

In the sections that follow, this review paper delves deeper into each of these facets, providing a comprehensive analysis of the current state-of-the-art, potential applications, and the ethical dimensions of this fascinating field. Ultimately, this research domain promises not only to deepen our understanding of human behavior in the digital age but also to guide us in utilizing this knowledge for the betterment of individuals and society at large.

## 2. DATA SOURCES

2.1 Social Media Posts:

- Social media posts, including text, images, and videos, serve as primary sources of data. Textual content can be analyzed for sentiment, linguistic style, and personality traits, while image and video data can provide insights into users' emotional expressions (Blachnio et al., 2013).

2.2 User Interactions:

- Interactions on social media platforms, such as likes, shares, comments, and messages, can reveal cognitive and emotional responses. Analyzing engagement patterns can help identify user preferences and emotional reactions.

2.3 User Profiles:

- User profiles on social media platforms often contain valuable demographic information. Mining this data can provide insights into the relationship between user characteristics and online behavior.

Social networks serve as a prolific source of data, offering a multifaceted view of individuals' digital lives. These sources range from textual content to user interactions and profile data, all of which combine to provide a comprehensive understanding of online user behavior (Blachnio et al., 2013).

**2.1 Social Media Posts:**

- **Textual Content:** The text-based content posted by users on social networks forms the core of data mining efforts. Researchers often analyze these textual inputs for sentiment, linguistic style, and personality traits. Sentiment analysis, for instance, categorizes text as positive, negative, or neutral, which helps gauge the emotional tone of user-generated content. Moreover, the linguistic style used in posts can provide insights into the writer's cognitive processes. For example, verbose and articulate language might be indicative of high cognitive abilities, while the use of certain words and phrases can reveal aspects of a person's personality (Hevner et al., 2004).
- **Multimedia Content:** Beyond text, social media users frequently share multimedia content, such as images and videos. This data can be a goldmine for emotional analysis. For instance, image recognition and video analysis tools can identify facial expressions, body language, and visual cues to determine emotional states like happiness, sadness, anger, and surprise. Understanding how users express their emotions visually can offer deeper insights into their digital personas.

**2.2 User Interactions:**

- Social networks are inherently interactive platforms, and these interactions yield a rich source of data. User responses to content in the form of likes, shares, comments, and private messages can be analyzed to understand cognitive and emotional responses. Patterns of engagement can reveal user preferences and the emotional reactions evoked by content (Blachnio et al., 2013). For example, an abundance of likes and shares on a post may indicate that it resonates emotionally with the audience. On the other hand, analyzing the content of comments can provide additional context, helping to gauge the depth and nuance of cognitive and emotional engagement.

**2.3 User Profiles:**

- User profiles on social media platforms are reservoirs of demographic information. This data includes details such as age, gender, location, educational background, and relationship status. While this information may not be shared explicitly by all users, many voluntarily provide these insights. Analyzing user profiles, when privacy settings permit, can provide a valuable link between demographic characteristics and online behavior. For instance, researchers can explore how certain personality traits, cognitive processes, and emotional states correlate with specific demographic groups. This can be pivotal for targeted research and tailored content delivery.

These diverse data sources illustrate the multifaceted nature of social network data and highlight the potential for comprehensive analysis of user personality, cognitive processes, and emotional states. The integration of textual content, multimedia content, user interactions, and profile information provides a holistic understanding of how individuals present themselves, interact with content, and engage with their online communities (Hevner et al., 2004).

As the field continues to evolve, researchers are exploring innovative methods for data collection and analysis, capitalizing on the wealth of data that social networks offer. These sources collectively empower data scientists to embark on a journey of understanding the complexities of human behavior within the digital sphere, uncovering the motivations, thoughts, and emotions that drive our online interactions (Blachnio et al., 2013).

## 3. DATA MINING TECHNIQUES

3.1 Sentiment Analysis:

- Sentiment analysis techniques are used to classify text data as positive, negative, or neutral. This helps in understanding the emotional tone of user-generated content.

3.2 Personality Trait Analysis:

- Personality traits can be predicted by analyzing text content, such as social media posts, using methods like the Big Five personality model (Openness, Conscientiousness, Extroversion, Agreeableness, and Neuroticism).

3.3 Emotion Detection:

- Emotion detection algorithms use image and video data to identify facial expressions and body language to determine emotional states. Machine learning models can categorize emotions like happiness, sadness, anger, and surprise.

3.4 Social Network Analysis:

- Social network analysis tools help identify relationships, communities, and influential users within a social network. This provides insights into the cognitive and social aspects of user behavior.

Data mining techniques are the cornerstone of the process that transforms raw data from social networks into meaningful insights regarding personality, cognitive processes, and emotional states. These techniques leverage a combination of machine learning, natural language processing, and computer vision to unveil the hidden dimensions of user behavior and attributes (Caers et al., 2011).

**3.1 Sentiment Analysis:**

- Sentiment analysis, often referred to as opinion mining, is a powerful tool for evaluating the emotional tone of textual content shared on social networks. This technique involves classifying user-generated text as positive, negative, or neutral, thereby providing an overall sentiment score for a given post, comment, or message. Sentiment analysis algorithms often employ a variety of natural language processing methods, including text tokenization, sentiment lexicons, and machine learning models to categorize text (Caers et al., 2011). These models can not only reveal the emotional tone but also nuances in sentiment, such as sarcasm or irony. Sentiment analysis enables researchers to gain a deeper understanding of the emotional expressions and attitudes of social network users.

**3.2 Personality Trait Analysis:**

- Personality trait analysis aims to infer an individual's personality traits based on their textual content, particularly their social media posts. The most commonly used model for personality trait analysis is the Big Five personality model, which comprises five dimensions: Openness, Conscientiousness, Extroversion, Agreeableness, and Neuroticism (often referred to as OCEAN) (Hevner et al., 2004). Textual data are analyzed for linguistic cues and patterns that correlate with each of these personality traits. For example, the use of certain words or sentence structures can indicate extroversion or neuroticism. Machine learning algorithms are often employed to predict a user's placement on the Big Five personality spectrum.

**3.3 Emotion Detection:**

- Emotion detection techniques primarily focus on multimedia content, such as images and videos. Computer vision algorithms and deep learning models are used to analyze visual content and identify emotional states. Facial recognition technology can detect facial expressions, while image and video analysis can gauge body language and visual cues that indicate emotions like happiness, sadness, anger, surprise, and more. These techniques are instrumental in understanding how users express their emotions visually, adding a layer of emotional insight to the overall analysis of user behavior on social networks (Hevner et al., 2004).

**3.4 Social Network Analysis:**

- Social network analysis delves into the relationships and interactions between users within a social network. It goes beyond individual characteristics and content analysis to explore the collective behavior within a network. Techniques such as network graph analysis and centrality measures can reveal influential users, communities, and patterns of connection. This type of analysis helps researchers understand not only individual cognitive and emotional processes but also the dynamics of social influence, information flow, and the formation of online communities (Caers et al., 2011).

Data mining techniques continue to evolve, with the integration of deep learning, advanced natural language processing models (e.g., transformer models like BERT and GPT), and state-of-the-art computer vision algorithms. These advancements enhance the accuracy and depth of analysis, allowing researchers to uncover increasingly nuanced insights into the personalities, cognitive processes, and emotional expressions of social network consumers.

The successful fusion of these data mining techniques enables the exploration of the complex interplay between user-generated content, emotional responses, and social dynamics on digital platforms. This, in turn, offers valuable knowledge for a range of applications, from personalized content recommendations to mental health monitoring and support, as well as more effective and ethical advertising practices.

## 4. APPLICATIONS

4.1 Personalized Content Recommendations:

- Analyzing user characteristics enables social networks to recommend content that aligns with a user's personality, preferences, and emotions, enhancing user engagement.

4.2 Targeted Advertising:

- Advertisers can use data mining to deliver more relevant ads by understanding the cognitive and emotional states of users, improving ad effectiveness (Hevner et al., 2004).

4.3 Mental Health Support:

- Data mining can be employed to identify users who may be at risk of mental health issues by analyzing their posts and interactions. This allows for early intervention and support (Hevner et al., 2004).

The insights derived from data mining techniques applied to social network data have far-reaching applications across multiple domains. These applications leverage the understanding of personality, cognitive processes, and emotional states to optimize various aspects of human-computer interaction and societal well-being.

**4.1 Personalized Content Recommendations:**

- One of the most prevalent applications of this research is in the realm of content recommendation systems. By understanding the personality traits and emotional states of social network users, platforms can deliver personalized content recommendations (Caers et al., 2011). For instance, a user who frequently shares content related to adventure travel and exploration may receive recommendations for similar content or travel-related products. This personalization enhances user engagement and satisfaction, as it aligns content with individual preferences.

**4.2 Targeted Advertising:**

- Understanding the emotional and cognitive states of users offers advertisers a unique advantage in crafting highly targeted and emotionally resonant advertising campaigns. By analyzing user interactions and content, advertisers can tailor their messages to align with the emotions and interests of their target audience. For example, a retailer could launch an ad campaign aimed at users who have expressed excitement about a particular product or brand, effectively capitalizing on the emotional connection.

**4.3 Mental Health Support:**

- Data mining on social networks also has critical applications in mental health support and early intervention. By analyzing the posts and interactions of users, it's possible to identify individuals who may be at risk of mental health issues. Signs of depression, anxiety, or emotional distress can be detected through linguistic patterns, sentiment analysis, and changes in posting behavior (Caers et al., 2011). This data can then be used to provide early intervention or connect individuals with appropriate mental health resources.

**4.4 Education and Learning:**

- The insights gleaned from personality and cognitive analyses can be applied in educational contexts. Understanding how students learn, their cognitive preferences, and their personalities can inform the design of personalized learning experiences. Adaptive educational platforms can adjust content and teaching methods based on individual traits, promoting more effective learning outcomes (Hevner et al., 2004).

**4.5 Social Network Improvement:**

- Social media platforms themselves can benefit from data mining applications to improve user experience and community dynamics. By understanding the dynamics of user interactions and the emergence of online communities, platforms can make informed decisions about content curation, policy development, and the design of user-friendly features (Hevner et al., 2004).

These applications underscore the transformative potential of data mining in understanding and enhancing online interactions and user experiences. By harnessing the insights into personality, cognitive processes, and emotional states, we can create more engaging, personalized, and supportive digital environments.

However, it's crucial to emphasize the responsible use of this data and adhere to ethical considerations, especially regarding privacy and informed consent. Privacy and data protection regulations, such as GDPR (General Data Protection Regulation) and CCPA (California Consumer Privacy Act), play a significant role in shaping how data mining in the context of social networks can be conducted (Caers et al., 2011).

In summary, the applications of data mining in analyzing the personality, cognitive, and emotional features of social network consumers are diverse and hold great potential to improve online experiences, advertising practices, mental health support, education, and the overall quality of social networks. As technology continues to advance and our understanding of user behavior deepens, these applications are likely to expand and evolve in novel and impactful ways.

**5. ETHICAL CONSIDERATIONS**

Analyzing the personality, cognitive, and emotional features of social network consumers comes with ethical concerns, such as user privacy, consent, and potential misuse of personal data. Researchers and platforms must adhere to ethical guidelines and ensure the responsible use of data.

Data mining on social networks is a field fraught with ethical complexities, primarily due to the sensitive and personal nature of the data involved. It's crucial for researchers, platform providers, and policymakers to navigate these challenges with transparency, responsibility, and respect for user privacy and autonomy.

**5.1 Privacy:**

- User data on social networks often includes personal information and intimate details about individuals' lives. Ethical data mining practices necessitate a commitment to safeguarding user privacy. Researchers must anonymize and aggregate data to prevent the identification of individuals. Furthermore, informed consent is essential when collecting and analyzing user data, ensuring that users understand how their data will be used and have the option to opt out of data mining efforts (Blachnio et al., 2013).

**5.2 Informed Consent:**

- Obtaining informed consent is a fundamental ethical requirement when conducting data mining on social network users. Users should be fully aware of how their data will be used and the potential consequences of data analysis. Consent should be voluntary and informed, and users should have the option to withdraw their consent at any time (Caers et al., 2011).

**5.3 Data Security:**

- Protecting the security of user data is of utmost importance. Researchers and platform providers should employ robust security measures to safeguard the data being analyzed. This includes encryption, access controls, and secure storage practices. Data breaches can have severe consequences, including privacy violations and the misuse of sensitive information (Hevner et al., 2004).

**5.4 Fair and Unbiased Analysis:**

- Data mining should be conducted without bias or discrimination. It is imperative to ensure that algorithms and models used in analysis are fair and do not perpetuate biases based on race, gender, or any other protected characteristics. Bias in data mining can result in unjust and discriminatory outcomes (Hevner et al., 2004).

**5.5 Ethical Algorithms:**

- The algorithms and models used in data mining should be designed with ethical considerations in mind. This means that they should prioritize user privacy, fairness, and transparency. Researchers should continually assess and mitigate the ethical implications of the algorithms they employ.

**5.6 Transparency and Accountability:**

- Transparency is a key ethical principle in data mining. Researchers should be transparent about their methods, data sources, and results. They should also be accountable for the ethical implications of their work. Transparent reporting helps build trust and ensures that the research can be scrutinized and validated (Blachnio et al., 2013).

**5.7 Data Ownership and Control:**

- Social network users should have control over their data. They should be able to access, modify, and delete their data. Data mining should respect user ownership and control, and users should be informed about how their data is being used (Caers et al., 2011).

**5.8 Ethical Review:**

- Ethical review boards and committees should oversee research projects involving data mining on social networks. These bodies can assess the ethical aspects of research proposals and ensure that they comply with established ethical standards and guidelines (Hevner et al., 2004).

**5.9 Legislation and Regulations:**

- Data mining on social networks is subject to various privacy and data protection regulations, such as GDPR in Europe and CCPA in California. Researchers and platform providers should adhere to these regulations and incorporate their principles into their data mining practices.

**5.10 Public Awareness and Education:**

- Raising public awareness about the ethical implications of data mining is crucial. Users should be educated about how their data is used, and they should have the opportunity to make informed choices about their participation on social networks (Caers et al., 2011).

In summary, ethical considerations in data mining for analyzing personality, cognitive, and emotional features on social networks are of paramount importance. Researchers and stakeholders should prioritize privacy, transparency, fairness, and accountability to ensure that data mining practices are conducted responsibly and ethically (Blachnio et al., 2013). This approach not only safeguards user rights but also fosters public trust and confidence in data-driven research and technologies.

## 6. FUTURE DIRECTIONS

As technology and data collection methods continue to advance, the field of data mining for personality, cognitive, and emotional analysis on social networks will likely expand. Future research may focus on improving the accuracy of analysis, developing more robust privacy protections, and addressing the ethical implications of this work.

## 7. CONCLUSION

Data mining approaches for analyzing personality, cognitive, and emotional features of social network consumers have the potential to revolutionize the way we understand and interact with online communities. By responsibly harnessing the power of data, we can gain deeper insights into human behavior and use this knowledge for a wide range of applications, from personalized content recommendations to mental health support. Nevertheless, it is crucial to address ethical considerations and privacy concerns to ensure that this field continues to benefit society while respecting individual rights and well-being.

## REFERENCES


1. Aran, O., Biel, J.-I., & Gatica-Perez, D. (2014). Broadcasting oneself: Visual Discovery of Vlogging Styles. *Multimedia, IEEE Transactions*, *16*(1), 201–215.
2. Arrow, K.J. (1969). The Analysis and Evaluation of Public Expenditures: The PBB-System vol 1 U.S. Government Printing Office, Washington, DC, USA chap The Organization of Economic Activity: Issues Pertinent to the Choice of Market versus Non-market Allocation.
3. Bachrach, Y., Kosinski, M., Graepel, T., Kohli, P., & Stillwell, D. (2012). Personality and patterns of Facebook usage. In *Proceedings of the 3rd Annual Web Science Conference ACM, New York, NY, USA WebSci '12 pp. 24–32*.
4. Bachrach, Y., Kosinski, M., Graepel, T., Stillwell, D., & Kohli, P. (2014). Your Digital Image: Factors Behind Demographic And Psychometric Predictions From Social Network Profiles (Demonstration). In *Proceedings of the 13th International Conference on Autonomous Agents and Multiagent Systems (AAMAS)*, (Vol. 2014 pp. 1649–1650).
5. Back, M.D., Stopfer, J.M., Vazire, S., Gaddis, S., Schmukle, S.C., Egloff, B., & Gosling, S.D. (2010). Facebook Profiles Reflect Actual Personality, Not Self-Idealization. *Psychological Science*, *21*(3), 372–374.
6. Bai, S., Zhu, T., & Cheng, L. (2012). Big-Five Personality Prediction Based on User Behaviors at Social Network Sites. arXiv:http://arxiv.org/abs/12044809.
7. Balmaceda, J.M., Schiaffino, S., & Godoy, D. (2014). How do personality traits affect communication among users in online social networks *Online Information Review*, *38*(1), 136–153.
8. Barrick, M.R., & Mount, M.K. (1991). The Big Five Personality Dimensions and Job Performance: A Meta-Analysis. *Personnel Psychology*, *44*(1), 1–26.
9. Biel, J.-I., & Gatica-Perez, D. (2013). The YouTube Lens: Crowdsourced Personality Impressions and Audiovisual Analysis of Vlogs. *IEEE Transactions on Multimedia*, *15*(1), 41– 55.
10. Biel, J.-I., Teijeiro-Mosquera, L., & Gatica-Perez, D. (2012). FaceTube: predicting personality from facial expressions of emotion in online conversational video. In *Proceedings of the 14th International Conference on Multimodal Interaction ACM, New York, NY, USA ICMI '12 pp. 53–56*.
11. Blachnio, A., Przepirka, A., & Rudnicka, P. (2013). Psychological Determinants of Using Facebook: A Research Review. *International Journal of Human-Computer Interaction*, *29*(11), 775–787.
12. Buettner, R. (2014). A Framework for Recommender Systems in Online Social Network Recruiting. In *HICSS-47 Proc. pp. 1415–1424*.
13. Buettner, R. (2015). A Systematic Literature Review of Crowdsourcing Research from a Human Resource Management Perspective. In *HICSS-48 Proc. pp. 4609–4618*.
14. Buettner, R. (2016a). Getting a Job via Career-oriented Social Networking Sites: The Weakness of Ties. In *HICSS-49 Proc. pp. 2156–2165*.
15. Buettner, R. (2016b). Innovative Personality-based Digital Services. In *PACIS 2016 Proceedings. June 27 - July 1, Chiayi, Taiwan.*
16. Buettner, R. (2016c). Personality as a predictor of business social media usage: An empirical investigation of XING usage patterns. In *PACIS 2016 Proceedings. June 27 - July 1, Chiayi, Taiwan.*
17. Buettner, R., & Buettner, K. (2016). A Systematic Literature Review of Twitter Research from a Socio-Political Revolution Perspective. In *HICSS-49 Proc. pp. 2206–2215*.
18. Caers, R., & Castelyns, V. (2011). LinkedIn and Facebook in Belgium: The Influences and Biases of Social Network Sites in Recruitment and Selection Procedures. *Social Science Computer Review*, *29*(4), 437–448.
19. Campbell, D.T. (1957). Factors relevant to the validity of experiments in social settings. *Psychological Bulletin*, *54*(4), 297–312.
20. Cantador, I., & Fernández-Tobías, I. (2014). On the Exploitation of User Personality in Recommender Systems. In *DMRS '14 Proc.: Proceedings of the International Workshop on Decision Making and Recommender Systems no. 1278 in CEUR Workshop Proceedings pp. 42–45*.
21. Celli, F., & Rossi, L. (2012). The role of emotional stability in Twitter conversations. In *Proceedings of the Workshop on Semantic Analysis in Social Media Association for Computational Linguistics, Stroudsburg, PA, USA* (pp. 10–17).
22. Celli, F., & Rossi, L. (2015). Long Chains or Stable Communities? The Role of Emotional Stability in Twitter Conversations. *Computational Intelligence*, *31*(1), 184–200.
23. Chapanis, A. (1967). The Relevance of Laboratory Studies to Practical Situations. *Ergnomics*, *10*(5), 557–577.
24. Chapsky, D. (2011). Leveraging Online Social Networks and External Data Sources to Predict Personality. In *Proceedings of the International Conference on Advances in Social Networks Analysis and Mining (ASONAM) pp. 428–433*.

25. Chou, H.-W., Chang, K.-C., & Lin, Y.-H. (2012). Facebook and Google Usage in Taiwans College Students. In *Proceedings of the Eleventh Wuhan International Conference on e-Business paper 91*.
26. Cohen, J. (1988). Statistical Power Analysis for the Behavioral Sciences 2nd edn. Lawrence Erlbaum, Hillsdale, NJ, USA.
27. Hahn, E., Gottschling, J., & Spinath, F.M. (2012). Short measurements of personality – Validity and reliability of the GSOEP Big Five Inventory (BFI-S). *Journal of Research in Personality*, *46*(3), 355–359.
28. Halevi, T., Lewis, J., & Memon, N. (2013). A Pilot Study of Cyber Security and Privacy Related Behavior and Personality Traits. In *WWW '13 Companion Proceedings of the 22nd international conference on World Wide Web companion pp. 737–744*.
29. Hall, J.A., & Pennington, N. (2013). Self-monitoring, honesty, and cue use on Facebook: The relationship with user extraversion and conscientiousness. *Computers in Human Behavior*, *29*(4), 1556–1564.
30. Hall, J.A., Pennington, N., & Lueders, A. (2014). Impression management and formation on Facebook: A lens model approach. *New Media & Society*, *16*(6), 958–982.
31. Hevner, A.R., & Chatterjee, S. (2010). *Design Research in Information Systems: Theory and Practice*: Springer.
32. Hevner, A.R., March, S.T., Park, J., & Ram, S. (2004). Design Science in Information Systems Research. *MIS Quarterly*, *28*(1), 75– 105.
33. Hollenbaugh, E.E., & Ferris, A.L. (2014). Facebook self-disclosure: Examining the role of traits, social cohesion, and motives. *Computers in Human Behavior*, *30*, 50–58.
34. Hu, R., & Pu, P. (2010). *A Study on User Perception of Personality-Based Recommender Systems*.
35. Hu, R., & Pu, P. (2011). Enhancing Collaborative Filtering Systems with Personality Information. In *RecSys '11: Proceedings of the 5th ACM conference on Recommender systems*.
36. Hughes, D.J., Rowe, M., Batey, M., & Lee, A. (2012). A tale of two sites: Twitter vs. Facebook and the personality predictors of social media usage. *Computers in Human Behavior*, *28*(2), 561–569.
37. Iddekinge, C. H. V., Lanivich, S. E., Roth, P. L., & Junco, E. (2013). Social Media for Selection? Validity and Adverse Impact Potential of a Facebook-Based Assessment. *Journal of Management*, 1–25.