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ARTICLE

The nexus between social media use for wellbeing and use disorder: A clustering analysis and personas

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Abstract: This study employs clustering techniques to identify distinct social media user personas based on psychological traits and digital behaviors within UK and Arab samples. A total of 563 participants, 255 participants from the UK and 308 from the Arab Gulf Cooperation Council (GCC) were analyzed using k-means clustering on seven key variables: Conscientiousness, Neuroticism, Social Media Usage Frequency, Social Media Usage Competency, Fear of Missing Out (FoMO), Social Media Contribution to Social Wellbeing (SM Contribution to SWB), and Social Media Disorder (SMD). Three distinct clusters were identified in each sample: Engaged Digital Optimists, Anxious Social Connectors, and Selective Minimalists in the UK, and Digital Strategists, Digital Overdependent, and Hesitant Users in the Arab sample. The results highlight the inter-relations among personality traits, social media engagement patterns and digital wellbeing. Although the profiles in the Arab and UK samples were largely aligned, the differences highlighted cultural nuances in social media behaviors. These findings offer valuable insights for designing targeted interventions to promote positive social media use and enhance digital literacy.

Keywords: social media; social media disorder; social wellbeing, personality; fear of missing out; digital wellbeing

1. Introduction

Social media has become an integral part of modern life, shaping how individuals interact, communicate, and perceive themselves within digital spaces. These platforms offer opportunities for self-expression, social connection, and information-sharing (Abd Ellatif Elsayed, 2025). Beyond personal interactions, social media has also revolutionized global communication and strengthened community engagement while simultaneously introducing challenges such as misinformation, social isolation, and cultural conflicts. However, the psychological impact of social media is not uniform; rather, it is influenced by various individual factors, including personality traits, social media literacy, and patterns of engagement. While some users experience positive outcomes, such as enhanced social belonging and emotional support, others may be vulnerable to negative consequences, including fear of missing out (FoMO), problematic social media use (PSMU), and declines in overall wellbeing (Alutaybi, Arden-Close, et al., 2019). Recent evidence indicates that social media use can simultaneously promote wellbeing while contributing to conflicts with life priorities or problematic usage (Cemiloglua et al., 2025; Supti et al., 2025).

Wellbeing is a multi-dimensional construct encompassing individuals' cognitive and affective evaluations of their lives, including life satisfaction, positive affect, and the absence of

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negative affect (Diener, 2000). Traditionally, it has been conceptualized as subjective wellbeing, focusing on an individual's personal assessment of their happiness and life satisfaction (Teghe & Rendell, 2005). However, wellbeing extends beyond the individual to encompass the quality of one's social environment. Social wellbeing (SWB) captures an individual's sense of connectedness, contribution, and belonging within their social contexts (Keyes, 1998), encompassing dimensions such as integration, coherence, contribution, actualization, and acceptance. Importantly, social wellbeing is not confined to face-to-face interactions; it can also flourish within online communities. Social media platforms significantly influence users' experiences of social connection and societal participation. Research has demonstrated that engaging in supportive online networks can enhance self-esteem, alleviate loneliness, and promote psychological health (Lin et al., 2022; Luo et al., 2022).

The central aim of this study is to identify distinct social media user profiles based on personality traits (conscientiousness and neuroticism), usage frequency and competency, fear of missing out, social media disorder, and contributions to social well-being. Conscientiousness and neuroticism were selected because they represent two personality dimensions that are particularly relevant to digital behavior. Conscientiousness is generally associated with self-regulation, responsibility, and disciplined behavior, which may support more controlled and balanced engagement with digital technologies. In contrast, neuroticism is linked to emotional sensitivity and vulnerability to stress, which may increase susceptibility to problematic social media use and FoMO. A more detailed theoretical justification for focusing on these traits is provided in Section 2. In addition, we examine whether these profiles manifest similarly across UK and Arab populations, providing a cross-cultural perspective. By structuring the study around the identification of user profiles first and then exploring cultural similarities and differences, we emphasize that profiling is the primary focus, with cross-cultural analysis serving to contextualize these profiles rather than being treated as a separate objective.

Within this evolving digital landscape, digital wellbeing refers to the ability to sustain overall wellbeing in the midst of continuous digital engagement, balancing the benefits and risks associated with technology use (Gui et al., 2017). Digital wellbeing encompasses using technology in ways that promote mental health and empathy, including facilitating inclusive communication, such as through text-based platforms, that supports reflection, emotional connection, and accessibility for individuals with diverse needs (Weijers & Munn, 2021). Similar to how physical and emotional health are maintained through habits like sleep, exercise, nutrition, and social support (Chang de Pinho et al., 2024), digital wellbeing depends on intentional, balanced, and self-regulated interaction with digital tools (Abeele, 2020). Given the centrality of social media in digital life, how individuals engage with these platforms directly influences their wellbeing. When approached consciously and competently, social media use can foster feelings of belonging, connectedness, and access to resources that support flourishing (Gudka et al., 2023; Weijers & Munn, 2024). Conversely, compulsive or socially comparative use can lead to emotional exhaustion and displacement of vital offline activities that nurture holistic health (Qin et al., 2024). Digital wellbeing should not be viewed as separate from general wellbeing; rather, it represents a contemporary and integral aspect of overall wellbeing, reflecting the important role digital experiences play in people's lives today (Abeele, 2020). Investigating how social media shapes digital wellbeing, and in turn broader psychological health, is essential to addressing the complex mental health challenges of today's digitally connected societies, particularly across diverse cultural contexts.

Despite growing research on social media and wellbeing, little is known about how individual traits and digital behaviors interact across diverse cultures. Most studies focus on

Western populations and treat these factors separately, leaving a gap in understanding underrepresented groups. This study addresses that gap by identifying distinct social media user profiles in Arab and British populations, examining personality traits (conscientiousness and neuroticism), fear of missing out, usage frequency and competency, social media disorder, and contributions to social wellbeing. Through a cross-cultural, data-driven approach, the research uncovers patterns of engagement and vulnerability, emphasizing culture's role in shaping digital wellbeing.

The Arab and British samples were selected to support a theoretically informed examination of whether patterns in social media use and social well-being differ across two cultural contexts, rather than to further privilege Western populations. Much prior research in this area has been conducted primarily within what is commonly classified under the WEIRD acronym (Henrich et al., 2010), with relatively limited inclusion of Arab samples using comparable measures and analytical frameworks. The British sample, therefore, serves as a theoretically grounded reference context, enabling an assessment of whether similar or different patterns emerge when the same framework is applied to an underrepresented Arab sample. Drawing on Hofstede's cultural dimensions, the two contexts are known to differ on individualism-collectivism, power distance, and uncertainty avoidance, dimensions that have been linked to social media engagement, social comparison, FoMO, and perceptions of social well-being. By including two samples within a single analytical framework, the study allows exploration of shared tendencies and potential contextual differences, addressing a gap in the literature that has largely relied on single-context analyses. Future research should extend this approach to additional cultural contexts that differ from both British and Arab frameworks, such as Asian and African populations, to further assess the generalizability of the identified patterns.

This paper is structured as follows: Section 2 examines the theoretical foundations underlying the study; Section 3 describes the methodology; Section 4 presents the results; and Section 5 discusses the findings concerning existing literature, acknowledges the study's limitations, and outlines suggestions for future research.

2. Theoretical background

2.1 Personality traits and social media engagement

Personality traits are fundamental in shaping online behaviors, influencing how individuals engage with social media (Kircaburun et al., 2020), regulate their interactions, and experience its psychological effects. Personality traits are enduring characteristics that shape an individual's patterns of thinking, feeling, and behaving. These traits are commonly categorized within frameworks such as the Big Five Personality Traits, Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism (Rammstedt & John, 2007). For example, Neuroticism stands out as a key predictor of Problematic Social Media Use (PSMU), as it is the personality trait most commonly linked to this behavior (Marciano et al., 2020). Individuals high in Neuroticism tend to experience emotional instability, anxiety, and impulsivity (Martin et al., 1983), often turning to social media as a coping mechanism for stress and negative emotions, which can lead to unintentional overuse and increased dependency (Bowden-Green et al., 2021). Additionally, high Neuroticism has been linked to increased FoMO (Balta et al., 2020), a psychological factor that drives individuals to check social media excessively to avoid feeling left out. A study found that FoMO mediates the relationship between neuroticism and PSMU, with full mediation in the European sample and partial mediation in the Arab sample (Alshakhsi, Babiker, et al., 2023). Additionally, Neuroticism has been associated with FoMO, as research indicates it greatly heightens vulnerability to social influence (Saritepeci & Kurnaz, 2024). Individuals high in

Neuroticism may seek validation, reassurance, or emotional support online, making them more prone to compulsive engagement with social media platforms. Taken together, this evidence clearly indicates that Neuroticism is associated with more problematic social media wellbeing outcomes (Marengo et al., 2020; Meynadier et al., 2024).

Some personality traits play a protective role against excessive social media use. For example, Conscientiousness, which reflects self-discipline, organization, and impulse control, play a protective role against excessive social media use. Highly conscientious individuals are more likely to regulate their screen time, engage in purposeful rather than impulsive social media use, and exhibit greater self-control in online environments (Kothambikar, 2023). A study found that Conscientiousness negatively predicted social media addiction, suggesting that individuals high in Conscientiousness are less likely to develop addictive behaviors toward social media (Piko et al., 2024). Conscientiousness has also been shown to predict better social media-related wellbeing in diverse cultural contexts (Cemiloglua et al., 2025). Research suggests that individuals with high Conscientiousness are less likely to develop problematic social media habits because they prioritize responsibilities over digital engagement and are more mindful of their online behaviors (Kothambikar, 2023). In contrast, individuals low in Conscientiousness struggle with time management and self-regulation, leading to greater susceptibility to social media addiction (Marengo et al., 2020; Meynadier et al., 2024). Conscientiousness has generally been negatively associated with social media use (Wehrli, 2008), indicating that those with higher levels of this trait tend to engage more actively and meaningfully rather than compulsively. Findings linking Conscientiousness to social wellbeing and social dependency are mixed, with some studies indicating protective effects, while others suggest more context-dependent relationships (Marengo et al., 2020; Meynadier et al., 2024).

2.2 Balanced social media use and social wellbeing

While highly conscientious individuals regulate their digital engagement, those with weaker self-control are more vulnerable to excessive and compulsive social media use (Alshakhsi, Chemnad, et al., 2023). However, balanced use of social media contributes to social wellbeing (SM contribution to SWB) by fostering social connections and providing access to valuable information and resources. Studies suggest that engaging with supportive online communities can enhance self-esteem, alleviate loneliness, and benefit psychological health, while proper use facilitates social interaction, information sharing, and self-expression (Wah & Ng, 2025). Moreover, social media functions as a powerful educational tool, providing access to resources on mental health, career growth, and other enriching topics (Naslund et al., 2020; Oluwatosin Esther Ajewumi et al., 2024).

Previous research indicates that balanced social media usage frequency (SM usage frequency) reduces feelings of social isolation (Meshi et al., 2020; Primack et al., 2017). Additionally, it fosters a sense of connection with like-minded individuals (Supti et al., 2025; Twenge & Campbell, 2019). Platforms like Facebook and Instagram help users sustain meaningful relationships, especially in situations where in-person interactions are restricted, such as during the COVID-19 pandemic (Choi & Choung, 2021).

2.3 Social media usage competency and digital self-regulation

Beyond frequency of use, social media usage competency (SM usage competency) plays an important role in determining its psychological impact. Individuals with higher social media literacy and self-regulation skills are more adept at managing their engagement (Galindo-Domínguez et al., 2025). Competent users critically assess online content, set healthy boundaries, and leverage social media for educational and professional development (Alonzo et al., 2023; Galindo-Domínguez et al., 2025). Higher competency in digital engagement and networking fosters access to valuable information, career opportunities, and skill-building resources, enabling users to maximize the benefits of online platforms (Kettunen et al., 2015; Molerov et al., 2020), while minimizing potential risks. By exercising control over their digital interactions, they are less likely to experience the detrimental effects of social media, including heightened FoMO, emotional distress, and poor security behaviors. In fact, recent empirical evidence indicates that problematic social media use is associated with increased exposure to cybersecurity risks and a higher likelihood of cybercrime victimization (Marttila et al., 2021). Deutrom et al. found that during remote work conditions, higher loneliness and lower life satisfaction predicted greater problematic internet use, which in turn negatively impacted cybersecurity behaviors (Deutrom et al., 2021). Individuals with low competency struggle to regulate their usage, becoming more susceptible to problematic patterns of social media use. Poor digital self-regulation has been linked to increased social comparison, anxiety, and compulsive checking behaviors (Rebello et al., 2024). Building on the previous findings, individuals with higher social media competency tend to report lower levels of Social Media Disorder (SMD) and higher social wellbeing. Their ability to critically engage with content, regulate usage, and pursue purposeful interactions not only buffers against compulsive use but also promotes healthier, more enriching digital experiences.

2.4 Excessive social media use, FoMO, and social media disorder

While balanced social media use can support wellbeing, excessive use, especially non-essential use, has been linked to distraction, reduced productivity, emotional distress, social comparison, decreased face-to-face interactions, and increased stress (Aziz, Chemnad, Al-Harahsheh, Abdelmoneium, Bagdady, et al., 2024; Sadagheyani & Tatari, 2020). Frequent social media use has been consistently associated with heightened levels of FoMO (Ocklenburg, 2021). Social media platforms, particularly those with real-time updates and algorithm-driven content, expose users to a continuous flow of social events, peer interactions, and curated highlights of others' lives, fostering an environment where FoMO can thrive (Poleac & Ghergut-Babii, 2024). Studies have shown that individuals who engage in frequent social media use are more likely to experience anxiety and compulsive checking behaviors, as they seek reassurance and inclusion within digital social circles (Baker et al., 2016). This cycle of persistent digital engagement leads to emotional dependence, reinforcing the urge to stay constantly connected (Buglass et al., 2017).

Frequent social media use also increases the risk of SMD, often regarded as a behavioral addiction, it is marked by compulsive use, difficulty in disengagement, loss of control, neglect of offline responsibilities, and adverse effects on daily life (van den Eijnden et al., 2016). Excessive users experience withdrawal symptoms when offline and prioritize digital interactions over real-world responsibilities. The instant gratification of notifications and algorithm-driven content reinforces these behaviors, making self-regulation difficult (Song et al., 2004). Elements like push notifications, infinite content feeds, and gamified interactions are intentionally designed to engage users and maintain their attention, unintentionally leading to dependency (Kunkel et al., 2023; Lora et al., 2025). But thoughtful design, such as features targeting FoMO, can help mitigate these effects (Alutaybi et al., 2024). Consequently, frequent use can contribute to problematic patterns, particularly in individuals with poor impulse control. Excessive usage has been associated with negative psychological effects, such as increased anxiety, depression, and FoMO (Aziz, Chemnad, Al-Harahsheh, Abdelmoneium, Baghdady, et al., 2024). Regular exposure to idealized representations of others on platforms like Instagram can foster upward social comparisons, leading to increased body dissatisfaction and negative self-evaluations, which are linked to lower self-esteem and overall life satisfaction in users (Pedalino & Camerini, 2022; Taylor & Armes, 2024). Studies shows consistent effects of idealized images on body dissatisfaction and related wellbeing outcomes (Conti & Kovács, 2025; Ozimek et al., 2023). Moreover, spending excessive time on social media often displaces essential activities that support mental wellbeing, such as physical exercise, which is known to enhance mood and life satisfaction, along with adequate sleep and in-person social interactions (Hyde et al., 2013; Zishan Khan, 2022). These behaviors correspond to the criteria for SMD, including preoccupation, withdrawal, and displacement. However, social media usage competency can serve as a protective factor against these negative outcomes. Individuals with higher digital literacy and competency are better at recognizing and resisting algorithmic manipulation, curating their digital environments, and engaging in mindful social media consumption, reducing their susceptibility to addiction and its associated harms (Gong & Popescu, 2025; Simamora et al., 2024). Therefore, fostering social media literacy and self-regulation skills is essential for promoting digital wellbeing and mitigating the risks of excessive social media use. Complementary strategies, such as increasing exposure to greenspaces, have also been shown to support emotional wellbeing and encourage physical activity, particularly in children (Ward et al., 2016), highlighting the importance of balancing screen time with restorative offline environments.

2.5 Cultural gaps in social media and personality research

Although previous studies have provided important insights into social media usage and its psychological effects, they often analyze these aspects separately, failing to consider their potential interactions. Systematic literature reviews on PSMU (Rohan et al., 2021) and the relationship between FoMO and personality traits (Rozgonjuk et al., 2021) highlight that most research in this area has been conducted within Western populations. However, there remains a lack of exploration into how these dynamics manifest within Middle Eastern societies, particularly in Arab populations. Cultural norms, social influences, and varying degrees of digital literacy play a crucial role in shaping individuals' perceptions of vulnerability to FoMO, their experiences with problematic social media use, and their patterns of digital engagement.

Building on the theoretical evidence linking personality, FoMO, social media usage, and wellbeing, the present study seeks to identify distinct social media user profiles. While cultural differences may shape how these profiles appear, the primary aim is to understand the interplay of these factors across users, with the UK and Arab samples providing a comparative context. This leads to the following research question:

> **RQ1:** Can distinct social media user profiles be identified, based on personality traits (conscientiousness and neuroticism), usage frequency, usage competency, fear of missing out (FoMO), contribution of social media use to social wellbeing, and social media use disorder?
>
> **RQ2:** Do the identified social media user profiles differ between the Arab and UK populations?

3. Research method

3.1 Participants and procedure

Participants were recruited from the United Kingdom (UK) and the Arab Gulf Cooperation Council (GCC) through TGM Research (https://tgmresearch.com/), a multinational online research platform that operates on a panel-based subscription model. Individuals voluntarily register with the platform, complete a detailed demographic and background profile, and may then choose to participate in research studies for which they are eligible. For the present study, only panel members who met predefined selection criteria (e.g., age, country of residence, language background, and cultural self-identification) were invited to take part. Eligible participants accessed the study via a unique survey link hosted on SurveyMonkey, ensuring that responses were self-administered, anonymous, and that duplicate participation was prevented. The survey was accessible across computers, tablets, and smartphones. These two regions were chosen due to their distinct societal norms and ethical frameworks, providing a valuable basis for comparative analysis (Hofstede, 1984). The GCC countries were selected to represent the Arab sample because of their geographical proximity, strong political ties, and shared cultural values and traditions (Jhon, 1986). Furthermore, both regions possess stable political and economic conditions and have advanced significantly in digital transformation, shaping consumer behavior and business landscapes (Smith, 2020). An anonymized OSF repository link containing additional details for this broader research initiative is provided in the Data Availability Statement section of the manuscript.

The survey was designed and conducted using SurveyMonkey (www.surveymonkey.com), an online platform for questionnaire distribution and data collection. To ensure clarity and precision in survey items, the research team followed an iterative development process. The original survey was written in English and subsequently translated into Arabic using the back-translation approach recommended by Brislin (Brislin, 1970). A pilot study was conducted with 5 participants from the UK and 5 participants from the Arab region to identify ambiguous wording, improve item clarity, and ensure cultural appropriateness. Feedback from the pilot led to minor refinements to the survey instrument prior to deployment. Subsequently, a soft launch was conducted with 15 participants per region (UK and Arab) to evaluate survey flow, completion time, and data quality. During the soft launch, participants were also given the opportunity to comment on the survey items and overall experience, and this feedback was used to make further minor refinements to the instrument before full-scale data collection. Data from the pilot and soft launch were not included in the final analyses.

Eligibility criteria required participants to be at least 18 years old, born and currently residing in either the UK (including England, Scotland, Wales, and Northern Ireland) or the GCC (comprising Saudi Arabia, Qatar, Bahrain, Kuwait, Oman, and the UAE). Cultural self-identification was assessed through self-report screening criteria during recruitment. In addition to country of birth and current residence, participants were explicitly asked whether they self-identified with the cultural norms and values of the target group. Only participants who responded “Yes” to the question were included in the study to account for individuals who may not perceive themselves as aligned with the cultural framework of their country of birth or residence. For the UK sample, participants were required to confirm that they were born and currently residing in the UK, self-identified culturally as British in terms of norms and practices, and spoke English as their native language. These criteria were used to ensure alignment with the cultural norms, practices, and communication contexts relevant to the UK population. Equivalent self-identification criteria were applied to the Arab sample, including confirmation of self-identification with Arab cultural norms and practices, regional residence, and language background, with participants who did not self-identify with the respective cultural group excluded from the final sample, to ensure comparability across cultural groups. Informed consent was obtained from all respondents, and they were given the freedom to withdraw from the study at any stage. To ensure high data integrity, attention-check items were embedded throughout the survey. Rather than using overt or easily identifiable instructed-response items, the attention checks were designed to closely match the wording, length, and format of the substantive survey items to avoid drawing undue attention or disrupting response patterns. These items included semantically implausible statements followed by embedded accuracy instructions (e.g., *"I use social media while on mars, strongly disagree here"*), allowing assessment of attentive responding while maintaining consistency with the surrounding items. Capitalisation and punctuation cues were deliberately avoided (e.g., *mars*, *strongly disagree*, without quotation marks) to ensure that attention-check items visually resembled other survey questions. Participants who failed one or more attention checks were excluded from the final analysis. In addition, completion time was monitored, and responses completed in an unreasonably short duration were excluded. These procedures were implemented to enhance data quality while minimizing demand characteristics, in line with best practices in online survey research. Participants received monetary remuneration in accordance with TGM's panel rating system. Compensation was provided on a per-completed response basis, covering both participant incentives and platform service costs. Each completed response was remunerated at £9.77, consistent with the panel's standard rates.

The study was granted ethical approval by the Institutional Review Board (IRB) of the last author's institution.

Individuals identifying as non-binary or preferring not to answer were excluded from the final analysis due to insufficient sample size (less than 5 in each sample). Additionally, participants aged 60 and above were excluded from the UK dataset since an equivalent age group could not be recruited in the Arab sample. Demographic data indicate that individuals over 60 comprise only about 7% of the population in many Arab countries (Benamer, 2014). Ensuring a comparable age range was crucial for the validity of cross-cultural comparisons. As a result, the final dataset was limited to participants aged 18–60 years. The total sample consisted of 563 individuals, with 255 from the UK and 308 from the Arab GCC.

3.2 Measures

In this section, we will explain the measures used in this research. All questionnaires, available in both Arabic and English, were translated using the back-translation method (Brislin, 1970) and can be accessed through the Open Science Framework (OSF), as referenced in the Data Availability Statement of this manuscript.

3.2.1 Demographic measure

Participants were required to provide their age and gender. Age was recorded as a continuous variable in years, while gender was entered in an open-text field and later manually reviewed and coded by the authors. Both fields were mandatory for submission.

3.2.2 Personality traits

The study utilized the BFI-10 to measure personality traits (Rammstedt & John, 2007). This brief version of the Big Five Inventory assesses five key personality dimensions: extraversion, which reflects sociability and outgoingness; agreeableness, which indicates friendliness and trustworthiness; neuroticism, which represents emotional stability; openness, which measures receptiveness to new experiences; and conscientiousness, which reflects goal orientation and determination, with each trait assessed using two items. Participants rated their responses on a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). Conscientiousness and Neuroticism were selected due to their robust associations with self-regulatory behavior, emotional reactivity, and susceptibility to problematic digital engagement, which are central to social media disorder and well-being outcomes (Meynadier et al., 2024).

3.2.3 Social media usage frequency and social media usage competency

In this study, Social Media Usage Frequency (SM Usage Frequency) and Social Media Usage Competency (SM Usage Competency) were measured using bespoke, self-developed questions. SM Usage Frequency was operationalized as the frequency of active social interaction on social media platforms. It was assessed with the question: *"How often do you actively interact with others on social media (e.g., commenting on posts, messaging, voice or video calls)?"* This approach was adopted to distinguish socially interactive use from passive consumption (e.g., scrolling), which may have different psychological implications. Participants rated their responses on a 6-point Likert scale, ranging from 1 (very infrequently) to 6 (very frequently), with higher scores indicating more frequent social media engagement. Social media usage competency was defined as individuals' perceived ability to effectively perform core social media functions, including content interaction, communication management, group administration, and privacy control. SM Usage Competency was measured with the question: *"Please rate your competency concerning the use of social media and adjusting their settings, e.g., posting and commenting, replying privately, hiding/showing posts, creating and administering groups, adjusting privacy settings."* Participants responded on a 6-point Likert scale, where 1 indicated "*not competent at all*" and 6 indicated "*very competent*". This measure reflects participants' self-perceived ability to navigate and manage social media platforms effectively, with higher scores indicating greater competency.

3.2.4 Fear of missing out (FoMO)

To assess fear of missing out (FoMO), participants were presented with a definition in English for the UK sample and an Arabic translation for the Arab sample. The definition stated: "FoMO, or the fear of missing out, describes the anxiety of not being aware of events (either on social media or in real life) and the concern of missing opportunities or being unable to participate." Participants then rated their agreement with the statement: "I experience FoMO regarding what is happening on social media." Responses were recorded on a 10-point Likert scale, ranging from 1 (Strongly Disagree) to 10 (Strongly Agree), with higher scores reflecting greater FoMO levels.

3.2.5 Social media contribution to social wellbeing

The survey questions used in this study to assess Social Media Contribution to Social Wellbeing (SM-SWB) were adapted from the SWB Scale developed by Keyes (Keyes, 1998). This scale measures five key dimensions of SWB: social integration (a sense of belonging within a community), social contribution (perception of making a meaningful impact on society), social coherence (understanding the social world as structured and predictable), social actualization (feeling positively engaged with society), and social acceptance (recognizing and accepting others as they are). The SM-SWB scale used in this study consists of 15 items, with 3 items per dimension, adapted from Keyes for the social media context. In this study, the scale was modified to align with the online environment by adapting terms associated with social structures (e.g., replacing 'community' with 'online community') to better suit the social media context. To provide clarity, participants were presented with an introductory statement: "Regarding your social media experience, indicate the extent to which you agree with the following statements:" Examples of the item: "I do not feel I belong to anything I would call an online community" and "I feel close to other people in my online community." Responses were recorded using a seven-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). Scores for each dimension were derived by summing responses to the three corresponding items. The reliability of each dimension was evaluated using Cronbach's alpha, yielding values of 0.81 for the UK sample and 0.79 for the Arab sample, indicating strong reliability across both groups. The theoretical range for the SM-SWB total score is 18 to 102 for the UK sample and 31 to 100 for the Arab sample.

3.2.6 Social media disorder

The SMD scale (Eijnden et al., 2016) measures Social Media Disorder and comprises nine items addressing factors such as preoccupation, tolerance, withdrawal, persistence, displacement, problems, deception, escape, and conflict. An example item is: "...regularly found that you can't think of anything else but the moment that you will be able to use social media again?" Participants rated each statement on a 5-point Likert scale, ranging from 1 (Never) to 5 (Always). The total SMD score was obtained by summing all responses, with higher scores indicating a greater level of SMD. The scale has demonstrated strong internal consistency, with Cronbach's alpha reported between 0.76 and 0.82 (Eijnden et al., 2016). In the present study, Cronbach's alpha was 0.89 for the UK sample and 0.81 for the Arab sample. The theoretical range for the SMD total score is 9 to 39 for the UK sample and 9 to 45 for the Arab sample.

3.3 Data pre-processing

To begin our data analysis, we examined the relationships between Social Media Contribution to Wellbeing (SM Contribution to SWB), Social Media Disorder (SMD), and several individual variables across both UK and Arab samples, as illustrated in the Appendix (Figure 1S), available via the OSF link provided in the Data Availability Statement section. Before proceeding with the cluster analysis, we carried out a two-step data preprocessing procedure. The first step involved standardizing the datasets for both samples using the scale() function in R, which adjusts the numeric matrix by normalizing its columns. To evaluate the suitability of the data for clustering, we assessed the clustering tendency by visually comparing two matrices. The first matrix reflected the correlation-based distances between data points in the original dataset, calculated using the Spearman method through the get_dist() function in R. The second matrix, created with randomly assigned values, had the same dimensions as the original dataset. A side-by-side visual inspection of these matrices confirmed that the data displayed an appropriate structure for clustering, as shown in the Appendix (Figure 2S), available via the OSF link provided in the Data Availability Statement section.

3.4 Clustering Approach

We employed partition clustering to categorize observations into distinct groups based on their similarities within each sample. The clustering variables included conscientiousness, neuroticism, SM usage frequency, SM usage competency, FoMO, SM Contribution to SWB, and SMD. To achieve this, we applied K-means clustering, an unsupervised machine-learning technique that partitions data into a predetermined number of clusters, denoted by *k*. The goal of this algorithm is to maximize within-cluster similarity while minimizing between-cluster dissimilarity. For the analysis, we utilized the Hartigan-Wong method (Hartigan & Wong, 1979), which reduces within-cluster variance by calculating the sum of squared Euclidean distances from observations to the centroids of their assigned clusters. Observations were allocated to clusters that minimized the squared distance to their respective centroids, computed using the k-means() function in R's stats package.

Since K-means clustering requires specifying the number of clusters, *k*, in advance, we determined the optimal *k* using the NbClust package in R. This package provides 30 indices to evaluate and suggest the most appropriate clustering solution by assessing various *k* values, distance metrics, and clustering techniques presented in Table 1S (see in the Appendix, available via the OSF link provided in the Data Availability Statement section) (Charrad et al., 2014). To ensure the reliability of the clustering results, we took three additional steps. First, we tested multiple *k* values to compare the outcomes and avoid selecting an arbitrary number of clusters. Second, given K-means' sensitivity to the initial random placement of centroids (Ikotun & Ezugwu, 2022), we ran the algorithm five times with different initial centroid placements, selecting the configuration with the lowest within-cluster sum of squares. For added stability, we used 15, 25, 35, 45, and 55 random initializations, with 1000 iterations per run. Prior to k-means clustering, the distributions of the seven clustering variables were inspected using histograms and standardised scores within each sample. This inspection identified a total of seven isolated category values that occurred only once or twice within a given sample (one value for extraversion, agreeableness, and conscientiousness in the Arab sample; two values for neuroticism in the UK sample; and one value for openness in each sample). These observations represented 7 values out of 3,941 total data points across the clustering variables (563 participants × 7 variables), corresponding to 0.177% of all observations. These values were not substantively extreme and did not indicate invalid responding or multivariate atypicality. They constituted distributionally sparse category values that can exert disproportionate influence on Euclidean distance calculations after standardisation, despite their negligible substantive weight (Milligan & Cooper, 1988). To limit this influence while preserving the full analytic sample, the affected values were set to missing, and no participants were excluded from the analysis. This approach maintains sample size and cluster prevalence while addressing a recognised sensitivity of k-means to isolated leverage points (Hennig, 2008; Jain, 2010). Given the negligible proportion of affected observations and their dispersion across variables and participants, this procedure does not alter the distributions of the clustering variables or bias the resulting cluster solution.

4. Results

4.1 Data characteristics

The overview of the participants from the UK and Arab samples of this study is provided in Table 1. A Welch's t-test was conducted to test the null hypothesis that the means of the two independent groups were equal, and the alternative hypothesis was assessed using the Bayes Factor (BF10) with default priors (Stefan et al., 2019). UK participants showed higher scores in neuroticism and lower scores in conscientiousness compared to Arab participants. Arab participants also showed higher scores in social media usage frequency, FoMO, SM contribution to wellbeing, and SMD.

Table. 1 Descriptive Statistics Analysis of All the Variables for the UK and Arab Sample

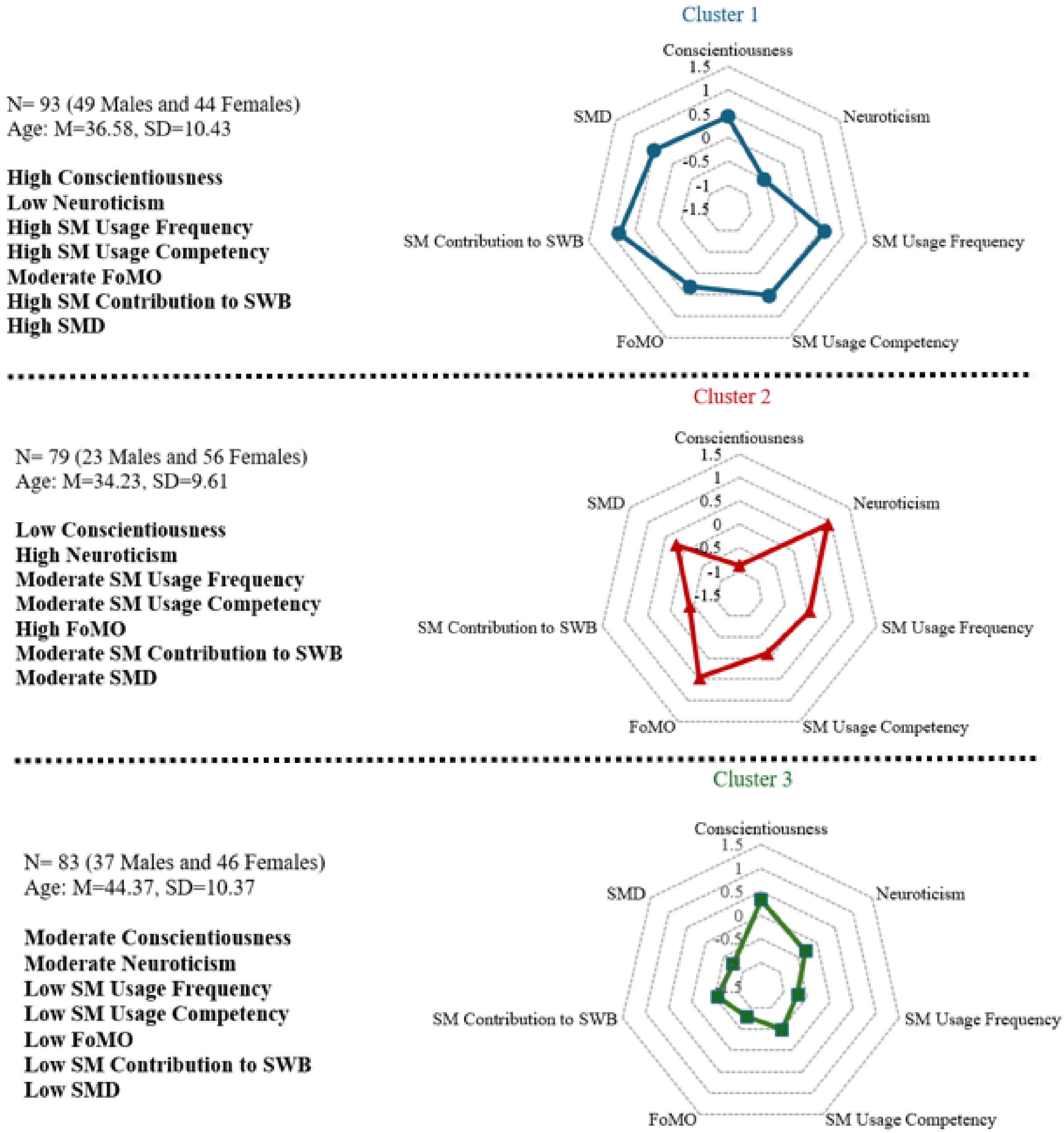
Variables		UK (N=255)	Arab (Arab=308)	t-test (*W, p-value, **BF10)
Gender	Males	109(42.75%)	139(45.13%)	
	Females	146(57.25%)	169(54.87%)	
Age	Males	37.92(11.30)	35.70(7.85)	-1.75, p=.08, BF_{10}=0.67
	Females	38.74(10.78)	32.63(7.29)	-5.79, p<.001, BF_{10}=9.81
Conscientiousness		7.79(1.67)	8.19(1.56)	2.88, p=.004, BF_{10}=5.59
Neuroticism		6.08(2.28)	5.14 (1.98)	-5.14, p<.001, BF_{10}>100
SM Usage Frequency		4.71(1.24)	5.18 (0.95)	4.99, p<.001, BF_{10}>100
SM Usage Competency		5.07(0.94)	5.11(0.84)	0.58, p=.56, BF_{10}=0.11
FoMO		4.85(2.87)	5.49(2.68)	2.68, p=.008, BF_{10}= 3.23
SM Contribution to SWB		62.41(14.55)	68.46(13.17)	5.12, p<.001, BF_{10}>100
SMD		16.63(6.49)	23.21(6.47)	12.00, p<.001, BF_{10}=32.90

Note. * Negative values for Welch's test indicate a smaller mean for the Arab sample than the UK sample. **According to Lee & Wagenmakers (Lee & Wagenmakers, 2013) Classification scheme, BF10 >100 provides extreme evidence for the alternative hypothesis (H1), 30-100 – very strong evidence, 10-30 – strong evidence, 3-10 moderate evidence, 1-3 and 1/3-1– anecdotal evidence, 1 – no evidence.

4.2 Result of Cluster Analysis Characteristics

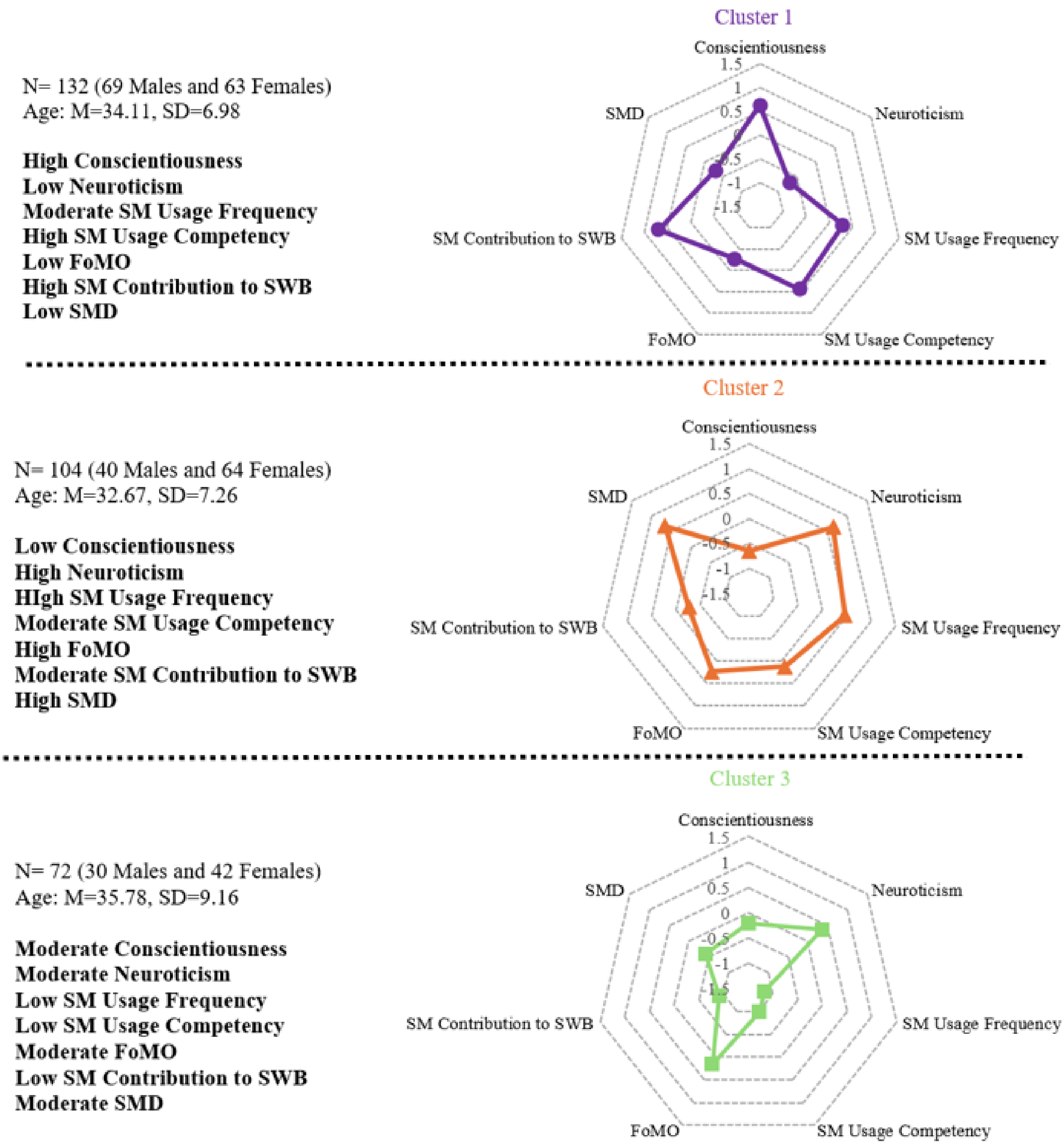
Our analysis aimed to identify the optimal number of clusters, and using the majority rule, we determined that three clusters provided the best solution for both the UK and Arab samples (see in the Appendix, available via the OSF link provided in the Data Availability Statement section). Figures 1 and 2 present the defining characteristics of these clusters. For the UK sample, three clusters were identified based on Conscientiousness, Neuroticism, SM usage frequency, SM usage competency, FoMO, SM Contribution to SWB, and SMD. Cluster 1 is characterized by high conscientiousness, low neuroticism, and high social media usage frequency and competency, with individuals experiencing moderate FoMO and high SM contribution to SWB and SMD. In contrast, Cluster 2 consists of individuals with low conscientiousness and high neuroticism, displaying moderate social media usage and competency but experiencing high FoMO, leading to moderate levels of SWB contribution and SMD. Lastly, Cluster 3 represents a more balanced profile with moderate conscientiousness and neuroticism, coupled with low social media usage, competency, FoMO, SM contribution to SWB, and SMD, indicating a more detached engagement with social media. These clusters suggest that personality traits and social media behaviors are closely intertwined, influencing individuals' online experiences and psychological wellbeing.

Figure 1: Cluster characteristics in the UK sample



Similarly, for the Arab sample, three distinct clusters were identified. Cluster 1 is characterized by high conscientiousness, low neuroticism, and high social media usage competency, with moderate social media usage frequency, low FoMO, high SM contribution to SWB, and low SMD. Cluster 2, on the other hand, exhibits low conscientiousness and high neuroticism, with high social media usage frequency, moderate competency, high FoMO, moderate SWB contribution, and high SMD, indicating a more emotionally reactive and highly engaged social media user group. Lastly, Cluster 3 represents individuals with moderate conscientiousness and neuroticism, low social media usage and competency, moderate FoMO, low SM contribution to SWB, and moderate SMD, suggesting a more detached social media engagement than the other clusters. These findings highlight the interplay between personality traits, social media behaviors, and psychological outcomes. The summary of the key characteristics of each cluster is available via the OSF link provided in the Data Availability Statement section.

Figure 2: Cluster characteristics in the Arab sample

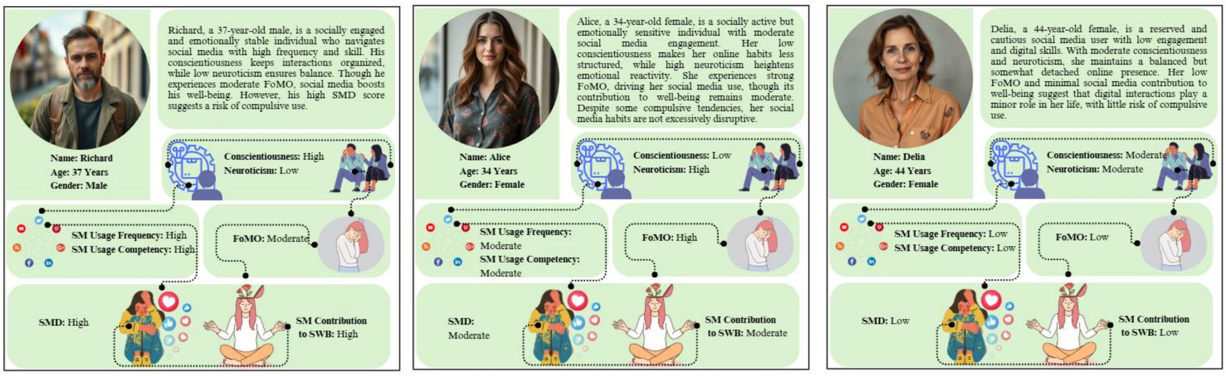


To examine the distinct characteristics of each cluster, we conducted a one-sample t-test, comparing cluster values against a baseline of zero for both samples (see Tables 3S and 4S in the Appendix, available via the OSF link provided in the Data Availability Statement section). The primary objective was to identify key attributes within each cluster, particularly those that significantly deviated from the average participant, either above or below the mean. These results are further illustrated through interval plots in the Appendix, available via the OSF link provided in the Data Availability Statement section, alongside detailed statistical analyses. To assess the validity of the clustering results, we used the silhouette coefficient (S) for the UK and Arab samples, both of which yielded an average silhouette width of 0.17. These values indicate a reasonable clustering structure, though some improvements could enhance cluster distinctiveness (see Figure 7S in the Appendix, available via the OSF link provided in the Data Availability Statement section).

4.2.1 From clusters to personas creation

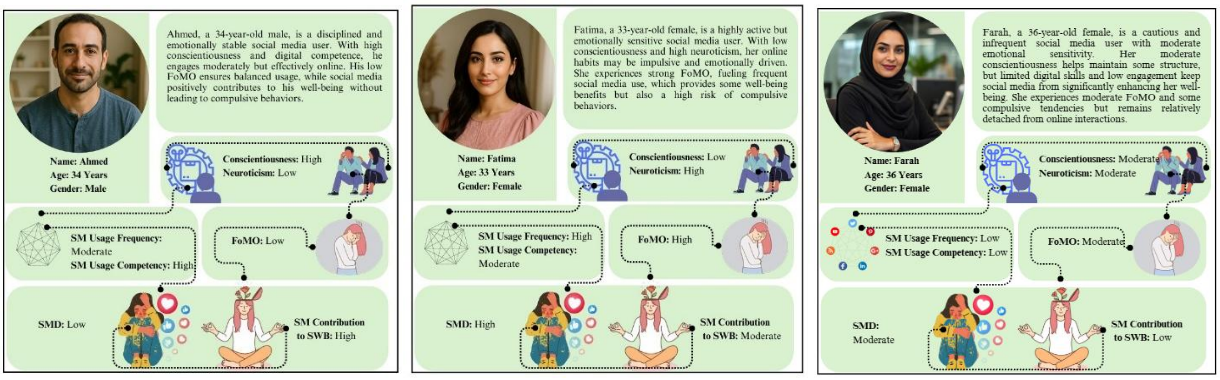
To facilitate understanding of the clustering results, each cluster is represented as a persona, an archetype that encapsulates the defining psychological and behavioral characteristics of individuals in that group. This approach bridges statistical insights and real-world relevance, offering an accessible way to interpret user diversity in digital behaviors. By visualizing data-driven user types, personas enable a wide range of stakeholders to engage with the findings: designers can prototype for specific needs, practitioners can tailor interventions, and policymakers can craft targeted awareness campaigns.

Figure 3: UK Personas (Richard: Engaged Digital Optimist, Alice: Anxious Social Connector, Delia: Selective Minimalist)



Note. Faces are AI-generated

Figure 4: Arab Personas (Ahmed: Digital Strategist, Fatima: Digital Overdependent, Farah: Hesitant User)



Note. Faces are AI-generated

Personas were developed based on the clustering outputs and carefully designed by the research team to accurately reflect the characteristics, behaviors, and patterns identified within each cluster. The structure, content, and descriptions of the personas were fully crafted by the researchers to ensure alignment with the underlying data and theoretical constructs. The design tool Canva (www.canva.com) was used for visual layout and presentation, while an AI-based image generation tool, Fotor (www.fotor.com), was used solely to create illustrative facial representations of the personas; these images were not used for analysis and do not depict real individuals.

5. Discussion

Personas are widely used in app development and policy design to define target groups and understand their unique characteristics. In the present study, cluster analyses identified three distinct social media user profiles in each sample (UK and Arab), differing in personality traits (conscientiousness and neuroticism), social media usage patterns, FoMO, contribution to social well-being, and susceptibility to problematic use. Representing these clusters as *personas* allows for a more intuitive understanding of the profiles and their behavioral tendencies. Creating detailed, evidence-based personas supports user wellbeing by tailoring digital experiences to varied emotional and cognitive needs (Farooq et al., 2025). For example, considering users' mental health and emotional states can help minimize stress and enhance engagement. Research has demonstrated how personas have been used to model the mental frameworks of aging populations in China, informing health app development (LeRouge et al., 2013), and to understand the specific needs of older adults with heart failure in user-centered intervention design (Holden et al., 2017). Similarly, a recent study addressing problematic social media use developed five behavioral archetypes that reflect diverse attachment styles. These archetypes were used to guide the design of personalized tools for behavior change, enhancing creativity, customization, and communication in the development process (Altuwairiqi et al., 2019). Personas are not intended to replace academic analysis, nor to distract from the empirical findings. Rather, they are a well-established design and communication tool in Design Science and Human-Computer Interaction (HCI), widely used to translate analytical results into interpretable representations that support sense-making, communication, brainstorming, and design decision-making (Nielsen, 2012; Pruitt & Adlin, 2006). As AI-based design and evaluation tools become increasingly common, personas provide a structured way to operationalize user differences, supporting testing of system acceptance, anticipated impact, and potential interventions, while also enhancing explainability and communication within AI-assisted systems (Salminen et al., 2020). Importantly, personas can also be conceptualized as agentive representations: users may be mapped to personas based on observed behaviour, or systems may infer personas dynamically and adapt content, interactions, or interventions accordingly. In the following, we discuss each persona in detail, highlighting their distinctive characteristics and potential implications for social media awareness and behavior change strategies.

5.1 Persona descriptions and analysis

5.1.1 UK persona

For the UK sample, three different clusters were identified, as shown in Figure 3. UK Cluster 1, named "Engaged Digital Optimist," is represented by Richard, a 37-year-old male with high conscientiousness and low neuroticism, traits make him well-organized, disciplined, and emotionally stable. This aligns with previous research, which indicates that highly conscientious individuals tend to be structured and goal-oriented, while those low in neuroticism demonstrate greater emotional stability (Ormel et al., 2012; Rhodes, 2024). His frequent social media usage, combined with strong digital competency, allows him to be highly engaged and adept at navigating online spaces. Research shows that students with high digital literacy are more confident and active in online environments, strengthening their self-efficacy, and leading to greater engagement across social, cognitive, and behavioral dimensions (Getenet et al., 2024). Despite experiencing a moderate level of FoMO, he is somewhat sensitive to social updates. A study found that FoMO is linked to social media use and highlights individuals with higher levels of FoMO tend to problematic social media use (Ocklenburg, 2021). But social media still contributes to his SWB. This suggests that he can control his usage patterns, engage meaningfully with content, and avoid the negative emotional toll that excessive FoMO can bring. However, Richard's high level of SMD presents an interesting contrast, as it suggests that despite his digital competency and ability to engage meaningfully with content, he may still struggle with compulsive social media use. Although Conscientiousness is often described as protective against problematic social media use, this case highlights that the effect of a single personality trait may be limited when considered in isolation. Instead, compulsive use may emerge from the combined influence of multiple factors, including frequent usage, moderate FoMO, and the engaging nature of social media platforms. This indicates that individuals with strong digital skills are not necessarily immune to problematic usage patterns. As the highly engaging nature of social media can reinforce habitual behaviors (Shanmugasundaram & Tamilarasu, 2023). His case highlights the duality of social media use; while it enhances wellbeing and self-efficacy, it can also contribute to excessive engagement that leads to dependence.

UK Cluster 2, named "Anxious Social Connector," is represented by Alice, a 34-year-old woman who exhibits low conscientiousness and high neuroticism, making her prone to emotional instability, stress, and difficulty regulating her social media usage. Research indicates that low conscientiousness impairs self-discipline, organization, and task management, exacerbating procrastination and making behavior regulation more challenging (Baumeister, 2017; Zhang, 2024), including social media use. Meanwhile, high neuroticism has been linked to increased emotional reactivity and vulnerability to stressors (Ormel et al., 2004). While she has moderate SM usage frequency and competency, her high FoMO drives much of her online behavior. Studies suggest that individuals with high FoMO engage in more frequent social media checking, driven by anxiety over missing out on social interactions or experiences (Alutaybi, McAlaney, et al., 2019; Przybylski et al., 2013). Despite this engagement, social media only moderately contributes to her SWB, as positive interactions are often counteracted by stress, social comparison, and emotional reactivity. Research highlights that while social media can enhance wellbeing through connectedness and social support (Charmaraman et al., 2025), individuals high in neuroticism experience more distress due to increased sensitivity to negative online interactions. Additionally, her moderate level of SMD suggests some problematic usage patterns, though they have not yet reached a severe level. However, her low conscientiousness means she struggles with self-discipline, making it difficult to set boundaries and regulate her time online effectively. This highlights the interplay between personality traits and digital behaviors, reinforcing the need for self-regulation strategies to mitigate potential negative consequences of excessive social media engagement.

UK Cluster 3, named "Selective Minimalist," is represented Delia, a woman with moderate conscientiousness and neuroticism, exhibits a balanced but somewhat cautious approach to social media. Research suggests that conscientiousness is strongly associated with self-discipline and organization (Turiano, 2020), but individuals with moderate conscientiousness may exhibit some self-discipline and organization without actively seeking highly structured digital engagement. Her low social media usage frequency and low digital competency indicate limited engagement with online platforms, which could stem from either a lack of interest or reduced confidence in navigating digital spaces (Hernández-Martín et al., 2021; Stojanov et al., 2023). Her low FoMO suggests she is not pressured to stay constantly updated on social events or trends. Notably, her low social media usage is likely a key factor in keeping her away from developing SMD, as research shows that reduced time spent on digital platforms is associated with lower risks of compulsive use and problematic behaviors (Pieh et al., 2025). Additionally, her low digital competency contributes to her lower SWB, as studies indicate that individuals with limited digital skills may struggle to derive positive benefits from online interactions, reducing their sense of social connectedness and digital engagement satisfaction (Kwiatkowska & Wiśniewska-Nogaj, 2022; Michikyan et al., 2025).

5.1.2 Arab persona

The characteristics of the three clusters in the Arab sample reveal distinct personas that encapsulate their behaviors, motivations, and challenges, as illustrated in Figure 4. Arab Cluster 1 termed “Digital Strategist,” represented by Ahmed, a 34-year-old male, embodies a structured and emotionally stable approach to social media use. His high conscientiousness suggests that he is disciplined, goal-oriented, and mindful of his digital habits, while his low neuroticism indicates emotional resilience and low susceptibility to stress from online interactions that align well with previous existing studies (Ormel et al., 2004; Rhodes, 2024). Despite using social media moderately, his high SM usage competency enables him to navigate digital spaces effectively, ensuring his engagement is purposeful and productive. Ahmed's low FoMO means he does not feel pressured to stay constantly updated, allowing him to maintain a healthy balance between online and offline life. His high contribution to social media to SWB suggests that he uses these platforms to enhance his personal and professional life, such as networking, learning, or entertainment (Cai et al., 2025). Furthermore, his low level of SMD indicates that he does not engage in compulsive or problematic usage, reinforcing that his digital habits are well-regulated. His high conscientiousness and digital competency contribute to his ability to use social media in a structured and goal-oriented manner, enhancing his SWB. At the same time, his low neuroticism and low FoMO protect him from excessive engagement, reducing the risk of developing SMD.

Arab cluster 2 named “Digital Overdependent,” represented by Fatima, a 33-year-old female, exhibits a highly engaged but emotionally vulnerable approach to social media. Her low conscientiousness suggests that she struggles with self-regulation, leading to impulsive or unstructured online behaviors aligning with existing study (Baumeister, 2017). At the same time, her high neuroticism indicates a tendency toward emotional instability, making her more susceptible to stress, anxiety, and mood fluctuations influenced by digital interactions. Her high SM usage frequency, paired with moderate competency, suggests that while she is an active user, she may not always navigate online spaces with strategic intent. The high FoMO further reinforces the idea that she relies on social media for social validation and constant updates, potentially leading to compulsive behaviors. While her social media use contributes moderately to SWB, likely through social connection and entertainment, her high level of SMD suggests that excessive and emotionally driven usage patterns may negatively impact her daily life and mental wellbeing (Zsila & Reyes, 2023). The high FoMO and neuroticism contribute to her vulnerability to SMD, whereas the moderate social media contribution to SWB may stem from temporary positive reinforcement rather than sustainable digital wellbeing.

Arab Cluster 3, named “Hesitant User,” represented by Farah, a 26-year-old female, presents a cautious but somewhat susceptible digital profile. Her moderate conscientiousness suggests a balance between discipline and spontaneity, while her moderate neuroticism indicates that she experiences emotional fluctuations but is not highly reactive. Her low SM usage frequency and competency indicate limited reliance on digital platforms, which aligns with research showing that individuals with lower digital literacy often engage less actively online and may struggle with effective navigation (Getenet et al., 2024). Despite her moderate FoMO, suggesting some sensitivity to social updates, her low contribution of social media to SWB indicates that she does not derive substantial emotional or psychological benefits from online interactions, a pattern observed in individuals who passively consume content rather than actively engage (Agarwal & Mewafarosh, 2021). The presence of moderate SMD suggests early signs of maladaptive usage patterns, which could stem from passive scrolling behaviors rather than strategic engagement (Gritti et al., 2023). Her low social media usage and low digital competency contribute to her limited SWB benefits, while her moderate FoMO and passive consumption may play a role in her susceptibility to SMD.

5.1.3 Cross-cultural interpretation of the clusters' outcomes

An important finding emerges when comparing Cluster 1 across the UK and Arab samples. While both the UK and the Arab personas share high conscientiousness and low neuroticism, only the UK cluster shows elevated levels of SMD. This result was not predicted by the literature, which generally associates high conscientiousness and emotional stability with stronger self-regulation and lower susceptibility to problematic technology use (Kothambikar, 2023). The divergence suggests that the relationship between adaptive personality traits and maladaptive social media outcomes may be culturally contingent rather than universal (Markus & Kitayama, 1991). Within the UK context, intensive, productivity-oriented, and goal-driven engagement with social media (e.g., professional networking, content curation, and constant availability) may enhance social media-related wellbeing while simultaneously increasing habitual use and reliance on digital platforms (Dodemaide et al., 2022). A study by Schivinski et al. (Schivinski et al., 2020) found that intrapersonal motives and daily social media use significantly predicted problematic social media use, even after controlling for psychological wellbeing and self-esteem, suggesting that problematic use can emerge from routine engagement rather than psychological distress.

In contrast, the Arab "Digital Strategist" does not exhibit elevated SMD, despite similar personality traits and digital competence. This difference may reflect cultural variations in the social meaning and regulation of social media use. In collectivistic and relational contexts, social media engagement is often more closely tied to family, community norms, and shared expectations, which may impose informal boundaries on excessive use (Hofstede, 2001; Triandis, 2001). Additionally, lower FoMO in the Arab Cluster 1 may further buffer conscientious individuals from compulsive engagement, allowing them to maintain purposeful use without escalating into dependency. These findings underscore the importance of considering cultural context when interpreting the protective or risk-enhancing roles of personality traits in digital behavior.

5.1.4 Social media design recommendations based on user personas

Creating user personas offers a novel approach to understanding diverse social media behaviors, enabling more tailored and effective design recommendations. By segmenting users based on psychological traits, digital literacy, and engagement patterns, personas provide a structured framework for addressing specific needs and challenges. This enhances social media design by ensuring that interface features, content delivery, and engagement strategies align with user preferences. Additionally, these insights inform policies on digital wellbeing, guiding platform regulations to mitigate problematic usage, promote responsible engagement, and improve user experience.

Personas challenge prior assumptions by shifting the focus from generalized user behavior to nuanced, data-driven insights (Agam, 2024). Traditional approaches often overlook how personality traits, digital literacy, and psychological factors like FoMO and self-discipline shape social media use. For instance, individuals with high digital competency may still struggle with compulsive usage, while those with low engagement are not necessarily disengaged. This challenges the notion that high usage equates to addiction or that limited engagement reflects disinterest. By integrating personas into social media design and policy, researchers can move beyond one-size-fits-all solutions, fostering adaptive, user-centered strategies that promote wellbeing and meaningful online participation. By utilizing personas that reflect distinct population segments, this research enables the development of more personalized and effective interventions tailored to specific emotional and behavioral profiles (Farooq et al., 2025).

Based on the earlier discussion, the following table provides tailored recommendations for each person, ensuring design interventions align with real user behaviors.

Table 2. Design Recommendation

Sample	User Persona	Key Design Strategies	Typical Engagement Patterns	Primary Objectives	Preferred Interaction Style	Relevant Technologies
UK	**Richard: Engaged Digital Optimist**	FoMO-Adaptive Notification Controls, Behavioral Nudges for SMD Awareness	Frequent, confident, exploratory	Reduce compulsive checking, encourage self-regulation, and maintain digital wellbeing	Scheduled & batch notifications, subtle in-app reminders, and usage insights	Notification batching, behavioral analytics for screen time tracking, and context-aware digital wellbeing nudges (Fitz et al., 2019; Sobolev, 2021)
	Alice: Anxious Social Connector	Emotional Regulation Prompts, Time-Managed Engagement Controls	High engagement but emotionally reactive	Reduce stress and social comparison while fostering meaningful connections	Supportive and reassuring (mental wellbeing nudges, self-reflection prompts) Gentle reminders for breaks, structured time limits	Sentiment analysis, automated session time management
	Delia: Selective Minimalist	User-Friendly Interface & Confidence-Building Digital Literacy Support	Low engagement, selective participation	Improve digital confidence, enhance online engagement satisfaction, and promote meaningful	Simplified navigation, guided onboarding, and occasional skill-building prompts	Adaptive UI personalization, interactive digital literacy tutorials, and intuitive onboarding assistance (Yaseen et al., 2025)

Sample	User Persona	Key Design Strategies	Typical Engagement Patterns	Primary Objectives	Preferred Interaction Style	Relevant Technologies
Arab	**Ahmad: Digital Strategist**	Professional networking features, structured content discovery, productivity tools	Moderate engagement, goal-driven	Optimize productivity and professional growth	Informative and structured (task-oriented notifications, professional updates)	AI-assisted content curation, scheduling tools (Basheer, 2024)
	Fatima: Digital Overdependent	Screen time limits, digital detox incentives, nudges for offline activities	High engagement, impulsive interactions	Promote self-regulation and healthier usage patterns	Gentle and guiding (self-regulation prompts, usage summaries)	Digital detox apps, time-restricted browsing (Zhou et al., 2024)
	Farah: Hesitant User	Guided Digital Engagement & Passive Consumption Awareness	Low engagement, passive content consumption	Increase digital confidence, encourage mindful engagement, and reduce passive scrolling habits	Step-by-step onboarding, interactive guidance, and subtle engagement prompts	Passive scrolling detection with engagement nudges and digital literacy enhancement tools (Purohit & Holzer, 2021; Yaseen et al., 2025)

5.1.5 Recommendation for Personas' Use

The personas provide a concrete and interpretable representation of the clusters identified in our analysis, translating complex, multidimensional patterns into actionable insights. Each persona captures the core characteristics of its cluster, including personality traits (e.g., Conscientiousness, Neuroticism), social media behaviours (e.g., usage, competency, FoMO, SMD, SM contribution to SWB), and demographic attributes (age and gender) derived directly from the clustering results. Age and gender were not assigned arbitrarily, but selected to reflect the distributional patterns observed within each cluster. The inclusion of names, age, and gender is meant to support interpretability and usability, and these elements can be adapted; they are not intended as fixed or factual claims beyond the data. Persona representations vary across contexts and methodological choices, highlighting that the form of a persona, including how its description and accompanying photograph are constructed, is flexible rather than fixed (Nielsen, 2018). Illustrative elements such as names, facial representations, and dress style are included to enhance interpretability and usability and are explicitly not intended as literal representations of individuals.

Personas do not need to represent exact or one-to-one mappings of statistical clusters or results; rather, they may serve as flexible templates that summarise key patterns for interpretation and application. This aligns with established practices in human-computer interaction, human-centred design, and behavioural research. A study by Calde defines personas as fictional, detailed archetypes representing groups of similar users (Calde et al., 2002), and with

Salminen et al.'s framing of personas as representative constructs that support empathy and communication rather than strict segmentation (Salminen et al., 2022).

Personas bridge the gap between quantitative analysis and practical application, supporting design decisions (Tu et al., 2010). Recent research increasingly positions personas not only as user-centred design tools, but as actionable design artefacts that support decision-making in policy, healthcare, and social intervention contexts. Gonzalez de Heredia et al. showed how personas are now used in policy-making and healthcare, helping institutions such as the UK Government's Open Policy Making toolkit and organizations like TACSI communicate population needs and design appropriate responses (Gonzalez De Heredia et al., 2018). Policy design frameworks treat personas as design artefacts that guide the creation, evaluation, and communication of policy ideas by providing meaningful archetypes to test solutions against. Creating a persona allows readers to engage with the behavioural and psychological profiles holistically, which is difficult to achieve through numerical tables or cluster labels alone. The personas also function as living artefacts, which can be adapted or refined in future research, demonstrating the flexibility and applicability of our findings across contexts.

Besides the novelty of this research, this study also has several limitations. First, using self-reported data may introduce bias, despite efforts to maintain anonymity and provide participants with the option to withdraw. Additionally, while the UK and Arab samples offer valuable insights, the results may not fully apply to other cultural contexts. Variations such as age group differences, especially among female participants, could have influenced the results and warrant further exploration. The focus on quantitative data may fail to capture the depth of individual experiences, which qualitative methods could better explore. Another limitation lies in the current application of the personas. While they were generated from empirical data and provide a useful interpretive lens, their practical relevance for designers, therapists, or policymakers has not yet been validated. Future work should include stakeholder engagement to assess how these personas can effectively inform intervention design, counseling strategies, or public awareness efforts. This step is essential to ensure the personas are not only theoretically sound but also actionable in real-world settings.

6. Conclusion

This study demonstrates the relationships between personality traits, social media engagement, and psychological wellbeing. Our clustering analysis showed that higher conscientiousness is associated with healthier social media habits, while higher neuroticism is linked to more problematic engagement. Although related factors such as FoMO and social media disorder help explain variations in behavior, the primary findings emphasize how personality shapes engagement patterns and their psychological impact. The presence of distinct user personas in UK and Arab samples suggests that cultural factors influence social media behaviors and their psychological impact. These insights offer practical implications for promoting digital wellbeing, designing supportive online environments, and developing interventions to encourage healthier social media use. Future research could explore how these patterns evolve over time and across broader cultural and demographic contexts.

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Author contribution statement

The study was designed and supervised by RA, DA, and SA, who also conceptualized the research. SA and RA prepared the study materials, collected, cleaned, and scored the data. Statistical analysis was designed and performed by TIS and AY. AY supervised the statistical analysis and contributed to the methodology. GX validated the analysis and its methodology. The initial draft of the manuscript was prepared by TIS and then reviewed and revised by AY, DA, GX, SA, and RA.

Conflict of interest statement

The authors report no competing interests.

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Data availability statement

The dataset associated with this work is uploaded alongside the study design and appendix for this article at: https://osf.io/tsmy4/

Ethical approval

The study was granted ethical approval by the Institutional Review Board (IRB) of Hamad Bin Khalifa University.

Informed consent statement

Informed consent was obtained from all respondents, and they were free to withdraw from the study at any time.

AI statement

AI was used in a supervised manner solely for error correction, grammar improvement, and style refinement.

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