TikTok Usage in the UK and USA: Investigating the Role of Demographic Factors, Personality Traits, and User Motivation

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Abstract

Social media has been an everyday presence in the Western world for many years, and TikTok is no exception. Different factors could influence how we understand TikTok usage, such as personality and user motivation. However, the literature surrounding specific cultures and TikTok user motivation appears to be lacking in non-student samples from Western countries (Günlü et al., 2023; Tian et al., 2022). The present study used a quantitative approach to explore how demographic factors, personality traits, and motives for use could predict TikTok usage in individuals from the United Kingdom (UK) and the United States of America (USA). Three hundred sixty-one adults (74.8% female) between 18 and 68 years old (M = 28.72) participated in an online survey and self-reported their TikTok usage from the past week as (1) the number of hours spent on TikTok and (2) the number of times they opened TikTok. Usage in the past week was conceptualised in three time periods: day-time (6am to 10pm), night-time (10pm to 6am), and a combined total. Participants also completed measures to determine Big Five personality traits (Rammstedt & John, 2007) and motives for use scores (Scherr & Wang, 2021). Results were analysed using hierarchical regression analysis, comprising six models: three for each measure of usage with one for each time period. Age was the most significant predictor from demographic factors across all models, with younger users reporting significantly higher TikTok usage than older users. Openness was the most significant predictor of the personality traits, but the relationship was negative, indicating higher levels of openness are associated with lower levels of TikTok use. Escapist addiction was the most significant motive for use, with openness and escapist addiction both showing significant contributions to five out of six models. This study's findings have many methodological implications for future social media research and practical applications for marketing practitioners and mental health support providers.

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1. Introduction

With the ease of communication and creative freedom in how to conduct oneself online (Carr & Hayes, 2015), social media has become a constant presence in our everyday lives (Attrill-Smith et al., 2019; McMahon, 2019; Rogowska & Cincio, 2024). With approximately 5.04 billion social media users worldwide recorded in early 2024 (Petrosyan, 2024), *social media* typically refers to online platforms and tools which can be used to create, share, and exchange content, thoughts and opinions, and information with others (Orchard, 2019; Van Dijk, 2013). *Social networking sites* (SNS), also referred to as *social media platforms* (SMP), are designed to encourage social networking, as the name suggests, and their contribution to the real world is continuously evolving with updates and innovative features for current platforms or the development of new ones (Anderson, 2017; Carr & Hayes, 2015; McIntyre, 2014). SMP will be used to refer to social media throughout this thesis because when discussing forms of social media such as TikTok, using SNS may not refer to platforms, such as mobile phone applications (or apps). Regarding the Western world, as of 2023, approximately 92.6% of the population of the United States and 84.4% in the United Kingdom aged 18 and above are active on social media (Dixon, 2024a; Johnson, 2023). Therefore, it appears that social media is a fundamental part of how we behave, perceive the world, communicate with others, express ourselves and place our trust in technology (Barnes, 2015; Håkansson & Witmer, 2015; Pangrazio & Selwyn, 2018; Peck, 2008).

Despite the well-known popularity of current SMP, such as Instagram and TikTok, others were active and popular many years earlier than some are aware. One of the first known SMP was Six Degrees, launched in 1998 by a company in New York City, designed for family, friends, or acquaintances to send messages, post bulletin board items and receive email updates and notifications (Boyd & Ellison, 2007). The ability to add other individuals to their profiles to communicate with them appears to be an early example of 'friending' someone online (Seitz, 2023). Since earlier SMP such as Six Degrees or MySpace, the purpose of social media is typically focused on establishing and encouraging social interaction, networking and communication, usually by providing updates, viewing, creating, sharing user-generated content (UGC; Naab & Sehl, 2016; Santos, 2021), or sending messages between users (Quinn, 2019). In more current SMP, this purpose has expanded to the business world, specifically business, advertising, and journalism, with organisations bring able to reach audiences outside the parameters of television and radio (Akram & Kumar, 2017). However, some have argued that there is no single umbrella term for all forms of social media, particularly as new platforms are developed that may not fit current or past definitions (Obar & Wildman, 2015).

Following the early 2000s, more SMP began to emerge, such as LinkedIn, MySpace, Facebook, and Twitter, with MySpace and Facebook becoming the most visited SMP in the world in 2007 and 2008, respectively (McCarthy, 2008; Thelwall, 2008). At the time of writing, even more SMP have been developed, launched, and surpassed old records set by their predecessors. For instance, TikTok, one of the most recently popular SMP, has approximately 1.56 billion users worldwide as of January 2024, while Facebook is still the most used SMP worldwide, followed by YouTube, WhatsApp, Instagram, and TikTok (Dixon, 2024b). While Facebook has maintained its popularity due to its usability and features accessible to all ages and backgrounds (Sibona & Choi, 2021), some SNS in recent years have developed sub-platforms or new ones entirely to suit a specific audience which has resulted in consistent interest and popularity despite having fewer active users than Facebook, for instance (e.g. YouTube Gaming; Seitz, 2015). An example of this would be Twitch, an interactive live-streaming service focusing on all elements of entertainment, such as sports and music, but primarily gaming, with approximately 8.36 million streamers as of January 2024 (Anderson, 2018; Clement, 2024).

This has also been the case with SMP being developed and exclusive to specific countries. For example, WeChat, a Chinese instant messaging, social media, and mobile payment app, has grown in active users to approximately 80% of the country's population (Thomala, 2024). However, the application does not appear as well-known or popular outside of China despite being available in approximately 200 countries (Custer, 2016; Davies, 2023). An article by Custer (2016) discusses some of these reasons for WeChat's lack of popularity outside China, with the most prominent reason being that the app struggled to adapt to the needs of foreign markets. Other apps already launched at the time, such as WhatsApp, had already established a large following, with family and friends all using the same app, making adoption of WeChat more difficult. However, this did not appear to be the case with all country-specific applications, as some have been improved to adapt to different cultures over time, such as WhatsApp (Dixon, 2024c).

1.1. What is TikTok?

TikTok is a short-form video-based social media application originally released by Beijing-based ByteDance Technology in 2016 under the name Douyin (Kaye, Chen, et al., 2020). After a positive reaction from users in China, ByteDance later acquired Musical.ly, a social media app comprising short-form video sharing that was gaining popularity in the United States. In 2018, Douyin was rebranded for markets outside of China as TikTok (Ahlse et al., 2020), designed for users to create, watch, and share short-form videos (Anderson, 2020). Short-form videos typically last from a few seconds to one or several minutes, but there does not appear to be an agreed length of time across the literature (Kaye, Chen, et al., 2020; Wright, 2017; Zhang et al., 2019). For instance, TikTok videos tend to last 15 seconds to three minutes (Wright, 2017; Yang et al., 2024), but videos uploaded directly from the users' device can last up to 10 minutes since 2022 (Birney, 2022).

At the time of writing, TikTok's popularity has significantly increased to the most downloaded app in 2022 and is available in 39 languages across approximately 150 countries (Ang, 2022). TikTok is most popular amongst younger audiences, with 71% of users aged between 18 and 34 years (Ceci, 2023b) and 67% of teenagers aged 13 to 17 years (Vogels et al., 2022). Also, TikTok has successfully adapted to audiences outside of its country of origin and is third in the UK and fourth in the USA for brand awareness, with 92% and 89%, respectively (Kunst, 2023a, 2023b). TikTok use is permitted for those aged 13 years or older, but direct messaging (or DM) is only permitted for users older than 16 (Kaye, Chen et al., 2020). Users can create original content, call on other users to participate in challenges or engage with 'duetting' videos with user-friendly editing features such as lip-syncing, filters, and background music. Creating a 'duet' on TikTok is a feature that allows users to create a split-screen video to respond to, interact with, or compliment another user's video. The original video and user's video appears side-by-side on screen and play simultaneously (TikTok Help Center, 2025).

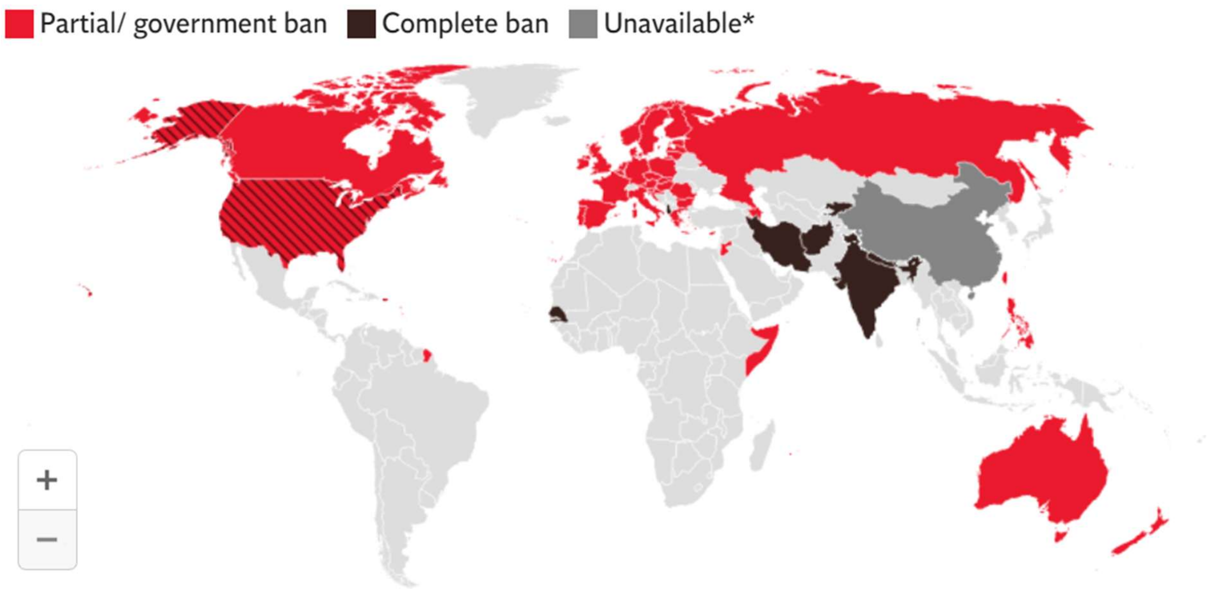
By using this variety of features, viewers are able to see content that matches their preferences on their 'For You' page, where they can imitate, interact with, or recreate the original video (Putro & Palupi, 2022). One method for creators to make and edit videos is using CapCut, another app owned by ByteDance, which TikTok encourages creators to use by adding the CapCut logo to creators' videos when they use it (Herman, 2023). While most TikTok users comprise adolescents, recent research has argued that TikTok use does include older age groups, with approximately a quarter of UK TikTok users being aged 75 and older as of early 2024 (Ceci, 2024a; Ng & Indran, 2022, 2023). Therefore, it seems necessary to investigate TikTok usage and user motivation for active TikTok users older than 16 because users below the age of 16 cannot access all of the app's features, such as direct messaging.

As shown by its increasing popularity within a short time frame, TikTok has made a significant global impact powered by UGC (Omar & Dequan, 2020). As past research suggests, it is a potent and accessible source of information for young people (Matsa, 2023; Smith, 2023), such as educational content (Hayes et al., 2020), political discussion or social activism (Literat & Kligler-Vilenchik, 2023), health information, or misinformation (Anderson, 2021), which particularly increased during and after the COVID-19 pandemic (Ostrovsky & Chen, 2020; Pew Research Center, 2023). However, TikTok has also been subjected in recent years to concerns surrounding cyberbullying, hateful content, and privacy (De Los Santos & Klug, 2021; Kumar & Goldstein, 2020; J. Wang, 2020; Weimann & Masri, 2020). On 'Public' TikTok accounts, all their content and posts are visible and can be shared by anyone who is or is not a TikTok user. However, on 'Private' TikTok accounts, the user can choose who they allow to follow their accounts and view their content; their content also cannot be shared. (TikTok Help Center, 2025).

National security concerns have also arisen with partial or government or full TikTok bans (see Figure 1) enforced in multiple countries (Ceci, 2023c; Cuthbertson, 2025; Maheshwari & Holpuch, 2023; Maiorca, 2023; Navlakha, 2023) and ongoing debates within their respective governing bodies (Kwande, 2023). If a country has enforced a full TikTok ban, all users from that country will be unable to download the app or access TikTok via an internet browser; the app will then be unable to update, reducing the app's quality and eventually becoming obsolete. (Zahn, 2025). If a country has a partial or government ban, government workers and military personnel are not permitted to install TikTok on their devices (Cuthbertson, 2025). In particular, the United States (US) government and citizens have expressed concerns about their nation's security surrounding TikTok and how it can access their data (Anguiano, 2023; McClain, 2023). On the other hand, approximately 37.36% of Americans are active TikTok users (Dean, 2023), and some have argued that banning TikTok would violate the First Amendment and freedom of speech (Pearlstein & Dellamore, 2023). Due to TikTok's global presence, exploring usage and user motivation in individuals from multiple countries may provide a richer insight into why and how TikTok is used cross-culturally.

Figure 1.

Countries where TikTok is either banned (black), partially banned (red) or unavailable (grey) as of April 2024 (Cuthbertson, 2025).



Notes: *ByteDance's Douyin is available in China instead of TikTok. ** Ban in USA (black and red) pending.

1.2. Comparing TikTok to other social media platforms

When measuring SMU, it is important to consider the relevance of a measure when applied to social media as an umbrella term or for specific platforms, such as but not limited to Facebook, Twitter, Instagram, TikTok, Snapchat, or YouTube. A major challenge in academic research is the need for keeping up with new social media platforms constantly being developed, new trends going viral, and new motivations behind usage forming (McLaughlin & Stephens, 2019). As a result, new measures for exploring TikTok use, for example, may pose challenges for research due to its unique format and user interface (UI; Syrjälä, 2024).

Unlike Twitter or Facebook, which are text-based platforms, or Instagram, which focuses on static images, TikTok is an exclusively video-based platform, which may require alterations in how TikTok usage and user motivation are measured (Gu et al., 2022). Some elements are similar to other platforms, such as the ability to like, comment on or share other users' content (Anderson, 2020), but some elements are unique to TikTok. For example, algorithms are the centre of the user experience (UX) on the internet and social media for both creators and viewers, and TikTok is no exception (Bishqemi & Crowley, 2022; Klug et al., 2021). Loosely defined as "…(a) set of rules that is used to…accomplish a task…" (APA Dictionary of Psychology, 2025), TikTok's algorithm is designed to find out more about the user.

Unlike, Facebook, Twitter, or Instagram, which prioritise exposure to content from friends or followed accounts (Burrell et al., 2019; Hitlin et al., 2019; Kim & Kim, 2018), TikTok's 'For You' page is designed around content discovery, where more granular behavioural data is collected (Kang & Lou, 2022). Examples include how long the user spent watching the video, or how many times they rewatched, liked, or shared it. This, in turn, is utilised by the algorithm to refine future recommendations for a more personalised feed independent from the user's social network (Anderson, 2020; Zhao, 2020). A report by Kemp (2025a, 2025b) found that the average TikTok user in the UK spent 42 hours on the app in November 2024, and the average USA user spending nearly 44 hours on TikTok (see Table 1). This was much higher than Instagram (8 hours 56 minutes for UK; 11 hours and 2 minutes for USA) or Facebook (15 hours and 38 minutes for UK; 16 hours and 24 minutes for USA).

Table 1.

Average time per month that active users spent using social media platform's android app in November 2024, split by country. (Kemp, 2025a, 2025b)

Time spent	UK		USA	
	Hours	Minutes	Hours	Minutes
TikTok	42	2	43	53
YouTube	19	0	24	43
Facebook	15	38	16	24
Snapchat	11	59	7	22
Instagram	8	56	11	02
WhatsApp	5	17	3	59
Line	5	06	2	50
X (formerly Twitter)	3	30	3	56
Reddit	3	30	4	09
Messenger	3	23	3	29
Telegram	2	30	2	36
Pinterest	1	4	1	26
LinkedIn	1	0	0	44

Note: Only includes data for a selection of the world's most used social media apps. Figures represent average time spent (in hours and minutes) per user, per month using each platform's mobile app on android phones in November 2024.

Once an SMP's algorithm determines what the user likes or dislikes, it can show more content that suits their preferences and thus increase their time spent on the platform (Bhandari & Bimo, 2020, 2022). In the case of TikTok, this tends to lead to what has been described as 'mindless scrolling' (Marek, 2023; Schellewald, 2021), where users begin to lose track of time in an endless stream of content specially chosen for them (Pltre, 2023). As SMPs continue to evolve, there has been growing debate about how users can stay well-informed on the nature of these platforms and their everchanging content. In particular, Wang (2022) highlighted the significant influence that algorithms have on shaping user experiences and the information they are exposed to. A leading argument is that the effectiveness of the algorithm causes TikTok users to become attached to the app in a way that could be construed as 'addictive' (Larssen, 2023; Zhang et al., 2019).

Another difficulty when comparing TikTok to other SMPs is the importance of active or passive SMU when engaging with the app. *Active social media use* (ASMU) is conceptualised in past social media research as posting content (e.g. photos or videos), interacting with content by liking or commenting, and one-to-one exchanges such as direct messaging (Pagani et al., 2011; Valkenburg et al., 2021), with some research expanding on these types of active use as social (e.g. directly communicating with friends) and non-social (e.g. creating content but not interacting with friends; Gerson et al., 2017). Examples of *passive social media use* (PSMU) include only viewing other users' posts, profiles, or comments (Ozimek et al., 2023; Peterka-Bonetta et al., 2021; Verduyn et al., 2020). In the case of TikTok, ASMU was more prominent during the COVID-19 pandemic as users were posting content or keeping in touch with one another due to physical isolation (Francisco & Ruhela, 2021).

Following the pandemic, as lockdown restrictions were lifted, PSMU appears more likely with the concept of 'mindless scrolling' as an activity while using the app (Şot, 2023). When compared to other visual SMP, such as Instagram, TikTok users experienced higher levels of flow states, such as time distortion (Roberts & David, 2023). Flow states are described as situations where individuals become so focused on what they are doing that nothing else is important, and they continue to engage in that activity despite potential negative consequences (Brailovskaia et al., 2018, 2021). Consistent with past research, this concept of flow states and time distortion coupled with easy and constant access to social media results in SMP users becoming engrossed when engaging in PSMU and thus losing track of time (Kendall, 2021; Kwak et al., 2014; Yang et al., 2024). While previous research shows time distortion predicts higher PSMU on other SMP, such as Facebook and Twitter (Marciano & Camerini, 2022), this is not the case with Instagram or YouTube (McGill et al., 2023; Roberts & David, 2023). It has also been argued that TikTok is psychologically different from other SMP and should be investigated further (Caponnetto et al., 2025; Vigil, 2023). For example, TikTok's personalised 'For You' feed, which adapts in real-time based on user behaviour such as pauses, replays and sharing, has been linked to increased dissociation and patterns of compulsive use (Schellewald, 2021; Marek, 2023). Therefore, to examine TikTok usage would allow for further comparisons with other SMP by highlighting differences and similarities in usage, self-reported measures, and motivations for use.

1.3. Research questions and hypotheses

The following research question and hypotheses have been identified in accordance with the aim of the research and based on the literature review presented in Chapter 2:

RQ1: How does self-reported TikTok use compare to in-app recorded use?

H1: There will be a significant difference between the number of hours users self-report spending on TikTok compared to in-app data.

H2: There will be a significant difference between the number of times users self-report opening TikTok compared to in-app data.

RQ2: To what extent does TikTok use vary by demographic factors, personality traits, and user motivation in a UK and USA sample?

H3: Demographic factors (age, gender, and nationality) will significantly predict TikTok use.

H3a: Younger users will show significantly higher levels of actual TikTok use than older users.

H3b: Female users will show significantly higher levels of actual TikTok use than male users.

H3c: There will be significant difference in actual TikTok use between UK and USA users.

H4: Extraversion, openness, neuroticism, agreeableness and conscientiousness will significantly predict TikTok use.

H4a: Higher scores in extraversion, openness, neuroticism will predict higher TikTok use.

H4b: Higher scores in agreeableness and conscientiousness will significantly predict lower TikTok use.

H5: Higher scores of motives for TikTok use (socially rewarding self-presentation, trendiness, escapist addiction, novelty) will significantly predict higher levels of TikTok use.

1.4. Research objectives

The present research aims to fulfil the overall objectives of this thesis by employing a quantitative approach to examine the extent to which demographic factors, personality traits, and motives for use predict TikTok usage among individuals in the UK and USA.

Objective 1. Adapt current assessment tools for TikTok usage within a UK and USA sample.

For this objective, a quantitative approach was used comprising a 19-item online survey: Motives for TikTok Use (Scherr & Wang, 2021). The purpose of this survey was to assess the strength of potential relationships between motives conceptualised in this measure and TikTok usage. The survey was distributed via two recruitment platforms: Sona Systems and Prolific.

Objective 2. Survey users' self-estimated TikTok usage in comparison to in-app recorded data.

To fulfil this objective, this followed the previously stated quantitative approach comprising an online survey, incorporating two types of self-report questions: estimated and in-app recorded use. The first questions asked participants how many hours they spent and how many times they opened TikTok in the past week. Then, the survey provided instructions into the settings section of the TikTok app to access their in-app recorded usage. This comprised the number of hours spent and number of times TikTok was opened in the past week in periods of day-time (6am to 10pm) and night-time (10pm to 6am).

Objective 3. Determine how demographic factors, personality and motivations for use predict TikTok usage in UK and USA users.

To achieve this objective, demographic factors were conceptualised as age, gender, and nationality. Personality was defined according to the Big Five personality traits by Goldberg (1990, 1993): extraversion, agreeableness, conscientiousness, neuroticism, and openness. Motivation for use was defined based on Scherr and Wang's (2021) motivations they defined as predictors of TikTok use: socially rewarding self-representation, trendiness, escapist addiction, and novelty. The measures used for personality and motivations for use were the 10-item Big-Five Inventory (BFI-10; Rammstedt & John, 2007) and the 19-item Motives for TikTok Use (Scherr & Wang, 2021), respectively.

All the above-mentioned factors were used as predictor variables in hierarchical regression analysis (Cramer, 2003), which aimed to explore the significance and strength of potential relationships between one or more predictors and two outcome variables: TikTok usage recorded in hours and the number of times the app was opened in the past week. The outcome variables were conceptualised during three periods of time: day-time (6am to 10pm), night-time (10pm to 6am), and a combined total. By using identified motivations for use specific to TikTok, the analysis also hopes to shed light on whether usage is predicted and, if so, to what intensity, by one or multiple motivations.

1.5. Summary

This chapter presented the work's context and the thesis' justification, research aims, research question, hypotheses, and objectives. It also provided a brief summary of the methods used to attain the study's objectives and answer the question and hypotheses proposed.

2. Literature Review

A review of the literature was conducted over a period of 5 months and used the following search engines: EBSCO, PubMed, Google Scholar, Science Direct, Research Gate, Scopus, Web of Science, and PsycINFO. Only English language publications were included, with no restrictions on country of origin or date of publication. Search terms included the following: TikTok, social media, usage, social networking sites, social media platforms, active use, passive use, subjective measures, objectives measures, pandemic, COVID-19, self-report, personality, traits, Big Five, motivation, uses and gratifications, OR short-form videos. Additionally, relevant papers were found by conducting a forward search (finding more recent articles that included the original referenced work) and backward search (reading the references of found articles). The literature review yielded a comprehensive insight, particularly conflicting studies which emphasised on the negative and positive implications of TikTok on the user, which is expanded upon in the following section.

2.1. The negative implications of TikTok

In the context of TikTok use, most of the current research tends to emphasise problematic, disorderly, or addictive TikTok use and its impact on its users engaging in both active and passive SMU (Masciantonio et al., 2021; Montag et al., 2021; Pan et al., 2023). Most literature comprises samples from adolescent, high school, or university students from a single country (Günlü et al., 2023; Qin et al., 2023; Sha & Dong, 2021; Tian et al., 2022). While these are appropriate age groups when investigating TikTok users, these studies neglect adult or older adult age groups who have been found to use TikTok for various reasons, such as improved social connections (Bibeva, 2021; Jarrar, 2023), or users not in education or from one or multiple countries (Deng et al., 2023; Hellemans et al., 2021; Jarrar, 2023). For example, some older adults may engage with TikTok as a way to combat loneliness or connect and communicate with family members (Li et al., 2022). Also, in the United States, nearly a quarter of adults aged 50-64 and 10% of those aged 65 and older reported using TikTok (Eddy, 2024; Gottfried, 2024), indicating that there is a presence of older adults on the app. So, not considering these age groups means ignoring a key group of TikTok users. However, including them, could improve our understanding of user motivation and behaviour. Also, problematic or addictive behaviours present in some SMP may not be present in others. Smith and Short (2022) found that loneliness was positively correlated with problematic Facebook use. However, loneliness has been found to have an inconsistent relationship with problematic use due to its associations with other psychosocial factors, such as self-perceived happiness or social anxiety (Baltacı, 2019).

Another factor which appears to link to concerns surrounding addiction is the cognitive processes of the user and how attention span has changed since the increase of social media use in everyday life (Chen et al., 2022; Wilmer et al., 2017). As the content shown on TikTok is constantly evolving due to the algorithm, this has led to increased time spent on TikTok (Jain & Hussenet, 2022). To achieve this, algorithm continuously updates the user's 'For You' feed with personalised videos based on their preferences. By consistently presenting the user with content that aligns with their interests, the platform encourages prolonged engagement, leading to increased time spent on the app (Putro & Palupi, 2022). By being able to explore their preferred content quickly and easily, it has been argued users experience more frequent releases of dopamine (Ijaz et al., 2022; Kohler, 2023), which is "most responsible for pleasure feeling" (Macit et al., 2018, p.883). However, dopamine releases can also happen when you are attracted to another person, eating food that you enjoy, or feeling good after exercising, all of which are everyday occurrences and not necessarily concerning behaviour (Baixauli, 2017; Greenwood, 2019; Small et al., 2003). With regards to social media, it has been argued that a dopamine loop could explain how releases of dopamine can increase SMU over time (Meshi et al., 2015;

Montag et al., 2017). A release of dopamine occurs after consuming social media content, but the mental sensation quickly disappears, thus resulting in increased SMU in order to experience the feeling again, and the cycle repeats (Wang & Wang, 2025). From this, SMU appears to show a prolonged effect on information comprehension, being able to multitask, and normative dissociation (Baughan et al., 2022; Pardede, 2019; Parry & le Roux, 2021). This is the case with TikTok due to its visual content being more likely to be engaged with, as opposed to text-based SMP, such as Twitter or Facebook (Chan & Allman-Farinelli, 2022; Slade-Silovic, 2018).

Another significant motivator for TikTok use, which has stimulated arguments over the potential addictiveness of the platform, is procrastination, a voluntary delay of an intended action by the individual despite their awareness of the delay potentially having adverse consequences (Ferrari & Tibbett, 2020; Sirois & Pychyl, 2016). Therefore, positive affective responses on a short-form video application, such as TikTok, are often fleeting, so the individual's time on social media unintentionally increases (Silver & Sabini, 1981; Xie et al., 2023). This appears especially prevalent in student populations, as they experience stressful, frustrating, or anxiety-inducing situations while at college or university (Pychyl et al., 2000). So, procrastinating on TikTok could provide them instant gratification and a way to escape reality or responsibilities (Brailovskaia et al., 2020; Nong et al., 2023; Uğur & Başak, 2018). However, this could negatively affect their overall mental health and well-being within and outside education (Hen & Goroshit, 2018; Rozgonjuk, Kattago, et al., 2018). In contrast, this concern over procrastination does not just apply to students. Multiple studies found similar elements contributed to procrastination behaviour on social media in adults aged 18 and older, which negatively affected their well-being. Some examples from past research suggest SMU causes individuals to avoid tasks (Alblwi et al., 2021), increases their feelings of anxiety (Eid, 2022), and can affect their sleep and thus their day-to-day lives or overall life satisfaction (Akhtar & Islam, 2023; Geng et al., 2021; Wang & Scherr, 2021). However, there has been debate around social media's role in procrastination behaviour. For example, it has been argued that habitual behaviours, such as the urge to frequently check social media, explains procrastination behaviour (Meier, 2021). This suggests a lack of self-control, where using social media becomes a default response in moments of boredom or disinterest (Du et al., 2019). On the other hand, past research suggests that social media is a means for individuals to procrastinate, such as going on social media during lectures or to avoid stressful or difficult tasks (Alblwi et al., 2019; Rozgonjuk, Kattago, et al., 2018). As explored by Alblwi et al. (2019), social media can become a coping mechanism to escape stressful situations. Understanding whether procrastinating behaviours are automatic habits or intentional avoidance can have implications when designing interventions for such behaviour, as implementing these may differ between individuals.

2.2. Comparing digital addiction to other addictions

The concept of digital addiction surrounding social media has been a significant topic of debate (Dauk, 2021), and TikTok has also provoked opinions on excessive or addictive use and how to regulate it (Evitts, 2022; Xu, Tedrick, et al., 2023). This appears to have led to inconsistencies across research and researchers' perceptions of how this form of SMU should be defined (Almourad et al., 2020; Singh & Singh, 2019). Some terms coined in research include but are not limited to the following in SMP: excessive (Yao et al., 2023), problematic (O'Day & Heimberg, 2021; Rogowska & Cincio, 2024), addictive (Yang et al., 2023), disorderly (Prakasha et al., 2023), overuse (Lakhan et al., 2023), or compulsive (Fontes-Perryman & Spina, 2021). Also, without referring to TikTok specifically, addictive behaviour towards other forms of media is prevalent in SMP, such as Facebook or Instagram (Balcı & Karaman, 2020; Brailovskaia et al., 2018), or more broadly, social media, smartphones, and the internet (Alshakhsi et al., 2022; Matsuzaki et al., 2023; Ryding & Kuss, 2020; Zhao & Zhou, 2021). Presently, while there are no diagnostic criteria for digital addiction or problematic SMU, the Diagnostic and Statistical Manual for Mental Disorders (DSM–5; American Psychiatric Association, 2013) has included

Internet gaming disorder (IGD) under "Conditions for Further Study." Similarly, the International Classification of Diseases version 11 (ICD−11; World Health Organisation, 2024) also now includes "Hazardous gaming" and "Gaming disorder" since its most recent revision. In this section, where necessary, SMU or TikTok use will be referred to as 'problematic' as opposed to 'addictive' to reflect the inconsistencies in research surrounding the classification of excessive SMU (Bányai et al., 2017). Past research such as Moretta and Wegmann (2025) outlines theoretical models propose diagnostic criteria for Social Media Use Disorder, highlighting similarities with pre-existing behavioural addictions, such as impaired control and functional impairment. However, this disorder is not currently recognised in the DSM-5 (American Psychiatric Association, 2013) or ICD-11 (World Health Organisation, 2024), which creates diagnostic validity concerns and adds to the ambiguity on the use of the term.

Other researchers have also argued that greater levels of SMU can highlight key signs of behavioural addictions, such as withdrawal (Almourad et al., 2020), which are also seen in other forms of addiction. Others, however, raise concerns regarding pathologizing common behaviours and argue that frequent use cannot always considered harmful (Billieux et al., 2015). Therefore, 'Addiction' or 'disorder' will be used when discussing conditions with existing diagnostic criteria or predefined concepts in research (e.g. drug addiction, gaming disorder, digital addiction). In contrast, using the term 'problematic' acknowledges the range of SMU behaviours that may result in negative consequences, but do not meet certain criteria to be considered an addiction.

One of the more challenging elements when investigating problematic SMU is overcoming contextual or methodological obstacles to develop valid measures (Shahnawaz & Rehman, 2020). For instance, Almourad et al. (2020) suggested usage style (e.g., time spent on the device), diagnostic criteria (e.g., withdrawal), and harmful consequences (e.g., harm to personal relationships) as characteristics of digital addiction. However, digital addiction appears as an umbrella term, and it has been argued that it should not be consistently applied to all types of digital addiction despite similar symptoms. For example, comparing social media to gaming or the internet, or comparing SMP to other SMP (Alhabash & McAlister, 2014; Cemiloglu et al., 2022). A reason for this could be as past research has argued that technologies such as the internet, gaming, and smartphones are an integral part of everyday life, understanding the activity the individual may be addicted to could depend on the medium which enables the activity (Alhabash & McAlister, 2014; Christakis, 2019).

With regards to TikTok in particular, research argues that problematic usage typically stems from a lack of self-control, specifically in young people (Yang, 2023). However, others suggest that TikTok's design plays a part, such as its complex algorithm or frequency of notifications, which keeps the users on the app for prolonged periods of time (Ebrahim, 2023; Li, 2023). As a result, accurate self-reports of TikTok usage could be difficult to obtain when measuring SMU (Boyle et al., 2022; Burnell et al., 2021; Coyne et al., 2023). It has also been argued that individuals who spend more time on other SMP have a greater difficulty self-reporting their usage more accurately (Ernala et al., 2020; Sewall et al., 2020). However, research suggests that self-reported estimates of SMU may differ significantly from actual usage data due to frequent under- or overestimating (Mahalingham et al., 2023; Parry et al., 2021). Subjective and objective measures for measuring SMU are later discussed in Section 2.4.

Furthermore, past research has shown that problematic SMU use can have significant consequences on physical or mental health, such as increased feelings of anxiety or depression (Lin et al., 2016; Ramsden & Talbot, 2024), long-term musculoskeletal discomfort (Ahmed et al., 2022; Gustafsson et al., 2010), tension headaches (Kandasamy et al., 2019), feeling disconnected from reality (Ali et al., 2015; Udayanga, 2023) or symptoms of nomophobia (the fear of being unable to access your mobile phone; Daei et al., 2019; Tuco et al., 2023). This could also potentially affect how the individual perceives their SMU, as time distortion effects, coupled with symptoms such as compulsion or overuse, may bias studies that rely on self-report measures (Lin et al., 2015; Rau et al., 2006). For example, individuals may report their SMU based on the perceived importance or urgency of being able to access their phone, rather than how long they actually spend using it. This could lead to an overestimation of SMU if emotional dependence is mistaken for higher levels of use (Kuss & Griffiths, 2017). It could also result in underestimates, in some cases, if users underreport their SMU to downplay potential problematic usage (Przybylski & Weinstein, 2012). However, it has been argued that if estimates of SMU are inaccurate, implications for physical or mental health could be misinterpreted, and for SMU research that does not employ objective data, it may be difficult to determine whether problematic SMU contributes to poor health outcomes (Çi̇çek, et al., 2024; Chugh et al., 2024).

It has also been argued that characteristics of digital addiction behaviours share some similarities with other forms of addiction (Lee et al., 2019; Rugai & Hamiliton-Ekeke, 2016). For example, individuals who are addicted to substances may display withdrawal-like symptoms, such as irritability or restlessness (Koob & Le Moal, 2008; Lee et al., 2019; Sistla et al., 2022). This could also be applied to those with digital addiction if they are unable to access their device, such as a computer or smartphone, or a particular SMP, for instance (Andreassen, 2015; Block, 2007; Hryniszak, 2019; Vaghefi & Turel, 2024). During the COVID-19 pandemic, lockdowns and forced social isolation also increased people's use of smartphones for work, study, or entertainment. As such, some have argued that the prevalence of digital addiction has risen dramatically following the impact of the pandemic (Li, Sun, et al., 2021; Siste et al., 2020). Also, is has been argued that digital addiction can be considered akin to other addictions through compulsive behaviour, which is considered a critical impairment for addictive behaviour (Dalley et al., 2011; Lee et al., 2019). Much like excessive drinking or gambling, compulsive and excessive technology use without consideration for the negative consequences could lead to a dependency on that technology and a lack of control over usage (Lapointe et al., 2013). Also, as individuals increase their SMU due to compulsion, this has been suggested to impact their daily life outside their social media or technology use (Clayton et al., 2015). For example, neglecting responsibilities and relationships or negatively impacting the individual's well-being are also consequences of digital addiction, which some have argued are significant to investigate further (Dahl & Bergmark, 2020; Kuss & Griffiths, 2011; Tran et al., 2017).

However, Almourad et al. (2020) suggested characteristics of digital addiction differ compared to other addictions. To use smartphones as an example, they are considered to be a constant presence in everyday life and are widely accepted socially (Lundquist et al., 2013; Turkle, 2011). They also be found to help users meet needs for communication, social connection, or access to services, while other addictions do not (Bert et al., 2013; Cho, 2015; Madianou, 2014). In contrast, other addictions, such as substances or gambling, tend to carry stigmas and are less socially accepted (Hing et al., 2013; Yang et al., 2017). Also, to identify addictions, the nature of the stimulus requires investigation. Regarding social media, stimuli may consist of notifications or a user's follower count, which can have a positive effect and increase usage and, as a result, the likelihood of addiction (Longobardi et al., 2020; Nasti et al., 2020). This does appear to possess similarities to gambling, such as rewards, which also encourages further gambling for the chance of a larger reward (Fauth-Bühler et al., 2016).

Additionally, substance addiction is reinforced by the positive reaction of consuming the substance in question, such as food or drugs; still, digital addiction is reinforced through relevant actions (Alavi et al., 2012). Regarding physical effects, digital addiction does not appear to show similarities to gambling, which is more associated with financial difficulties (Barnard et al., 2013). Substance use, on the other hand, does show some similarities to digital addiction in physical changes or health consequences as a sign of excessive use (Kurniasanti et al., 2019). For example, alcoholism is argued to increase chances of obesity, cardiovascular disease, and lethargy (Moglia, 2018), while physical effects of digital addiction are suggested to be poor sleep, eye strain, or musculoskeletal issues (Ahmed et al., 2022; Kandasamy et al., 2019).

However, the physical effects of alcohol addiction are claimed to be more immediate and, in some cases, more severe (e.g. liver disease or failure, pancreatitis; Edmondson, 1980; Moglia, 2018). In contrast, whereas the physical consequences of digital addictions, such as sleep disturbance or musculoskeletal problems, tend to develop over time from prolonged and continuous use (Ahmed et al., 2022; Small et al., 2020).

When digital addiction is compared to other addictions, it is important to be mindful of treating different addictions as the same, as there are some unique characteristics in digital addiction that are not present in other addictions (Almourad et al., 2020). Understanding TikTok or broader SMU behaviour construed as addictive, problematic or excessive is intrinsically complex. Also, past research presents possible explanations for how SMP use can pose a risk for problematic or addictive behaviour (Kuss & Griffiths, 2017). Still, it seems the idea that social media is addictive does cause debate in research, particularly regarding the use of the words: 'addictive' or 'addiction' (Xu, Tedrick, et al., 2023). For example, Cash et al. (2012) argued that SMP users develop symptoms which may reflect those of other addictive disorders, such as gambling. However, symptoms of digital addiction, such as withdrawal, may display parallels to offline forms of addiction but should not be treated as such. This is because it seems to be unclear whether these symptoms manifest as a result of an addiction which is yet to be conceptualised and, if so, whether the symptoms impair the individual's ability to function (Kardefelt-Winther et al., 2017). Therefore, it is necessary to consider everyday TikTok use without assuming positive or negative psychological effects to reduce the risk of overpathologizing everyday SMU or hastily establishing SMU as an addiction or disorder without further investigation (Almourad et al., 2020; Billieux et al., 2015).

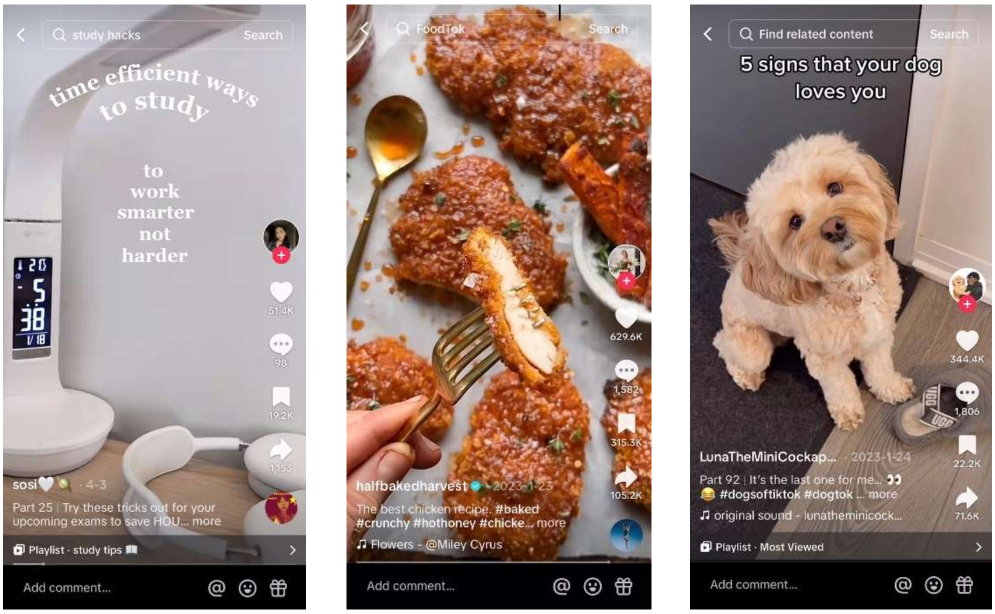
2.3. The positive implications of TikTok

Despite concerns surrounding TikTok use, it is a platform which also has an array of benefits it provides to its users. For example, since the COVID-19 pandemic in 2020, the awareness and popularity of TikTok in the Western world has increased significantly (Ceci, 2023a; Gottfried, 2024) with multiple benefits for users (McCashin & Murphy, 2022). TikTok became a source for mental health support, with creators and viewers finding and sharing information, advice, and words of encouragement with one another (Basch et al., 2022; Campana, 2022; Dong & Xie, 2022). Beyond mental health, general health and safety awareness related to COVID-19 was also shared through TikTok, with health organisations utilising the platform to distribute accurate information about healthcare support, preventive measures, and the virus itself while counteracting the considerable amount of misinformation also being shared on TikTok during this time (Basch, Fera, et al., 2021; Basch et al., 2020; Basch, Meleo-Erwin, et al., 2021; Li, Guan, et al., 2021; Southerton, 2021). It also provided support for educators and their students as institutions grew accustomed to remote learning, with creative ways to teach, distribute material and maintain student engagement (Bahagia et al., 2022; Pasaribu & Naibaho, 2021; Putri, 2021; Salasac & Lobo, 2022).

In the context of during and after the pandemic, TikTok also aided its users by enhancing opportunities for community building, creative expression, and business development or entrepreneurship (Flood, 2021; Johnson et al., 2022; Shao & Lee, 2020). It has been argued that during the pandemic, TikTok provided a much-needed source of comfort, entertainment and, for some, distraction during periods of isolation (Giancola et al., 2023; Şot, 2023; Xu, Wang, et al., 2023). These types of content typically comprised of viral dance challenges, comedy sketches, and lip-syncing or duetting trends to improve mood, alleviate boredom and reduce stress (Feldkamp, 2021; Griffiths, 2023; Iodice & Papapicco, 2021; Roth et al., 2022; Siano, 2021). Some types of content then encouraged community building based on personal preferences by using the word '-tok' (derived from TikTok), such as 'StudyTok, 'CleanTok', 'DogTok, 'FoodTok', 'CatTok', and 'BookTok' (see Figures 1 and 2) (Dahlgren & Enshagen, 2023; Flood, 2021).

Figure 2.

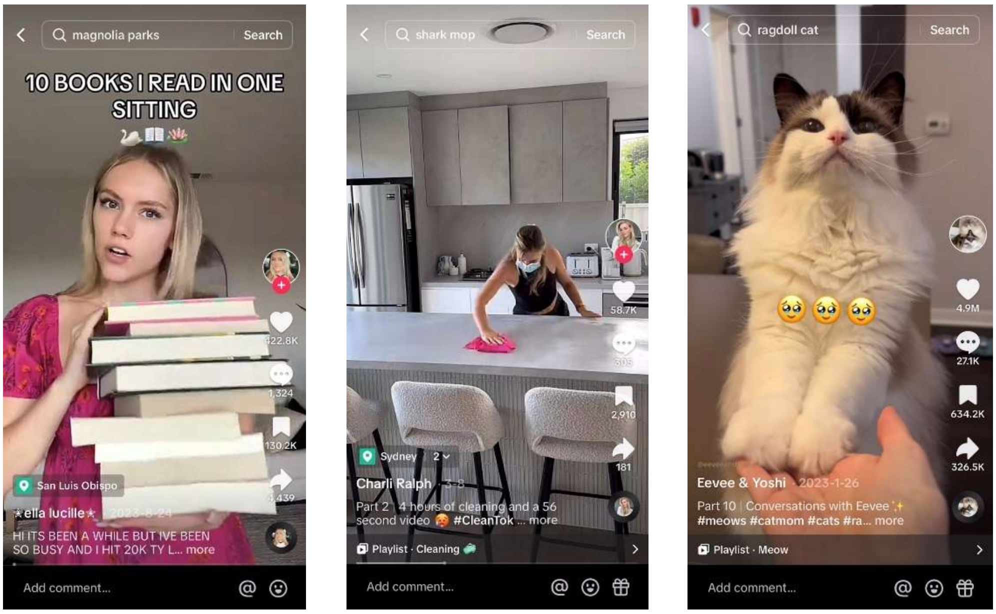
Screenshots of TikTok videos depicting examples of #StudyTok, #FoodTok, and #DogTok content.



Note: From left to right: #StudyTok (sosi 🤍 🪐, 2024); #FoodTok (halfbakedharvest, 2023); #DogTok (LunaTheMiniCockapoo, 2023).

Figure 3.

Screenshots of TikTok videos depicting examples of #BookTok, #CleanTok and #CatTok content.



Note: From left to right: #BookTok (✯ella lucille✯, 2023); #CleanTok (Ralph, 2024); #CatTok (Eevee & Yoshi, 2023).

With ‘BookTok’ as an example, the trend originated using a hashtag (#BookTok) which allowed creators to make their content more identifiable by the algorithm and reach their desired audience: fellow readers and book lovers (Merga, 2021). Their content typically comprised book recommendations, discussing character or story theories, and sharing jokes about the literature (Dezuanni et al., 2022; Harris, 2021; Wiederhold, 2022). Communities such as this become very prominent for TikTok users and their sense of identity, particularly students and young people, as they could easily meet others of similar minds who share the same joy of reading (Dezuanni et al., 2022; Jerasa & Boffone, 2021; Nagy, 2022).

While TikTok creators utilised the creative features of the app to share everyday hobbies or activities, such as reading or cooking, some creators also used TikTok to establish a business. The COVID-19 pandemic affected various employment sectors due to business closures, and employees being furloughed, vulnerable to job loss, or made redundant (Allas et al., 2020; Singh et al., 2021). Sectors such as travel, tourism, retail, and hospitality were particularly affected due to restrictions worldwide (Davahli et al., 2020; Roggeveen & Sethuraman, 2020; Škare et al., 2020), but TikTok provided opportunities to aid those in these industries. For example, individuals in the retail sector promoted products and services through endorsements and video marketing to go viral and increase views, followers, and therefore their customers (Hasim & Sherlina, 2022; Nair et al., 2022; Yao, 2021). For some TikTok users, being a content creator or influencer has become a source of income as a part-time or full-time role (Johnson et al., 2022; Tanachot, 2021). This also opened doors for other content creators, businesses, and influencers to collaborate with one another and raise each other’s social capital and thus their individual businesses (Coleman, 1988; Cui, 2021; Vega, 2021). While content creators and influencers have been able to earn an income through creative and accessible methods through social media (Andon & Annuar, 2023; Green et al., 2022), some have argued its shortcomings. For instance, Saini and Chourasiya (2023) stated that while utilising SMPs has taken away the organisational stress of content creation, it also increases the pressure of competition between creators and the need to constantly produce high-quality and attractive content (Arriagada & Ibáñez, 2020; Munro, 2022).

2.4. Measuring TikTok use

As TikTok use has increased since its release with 3.5 billion all-time downloads at the start of 2021 and was projected to reach approximately 15 million UK users in 2025 (Ang, 2022; Ceci, 2022), past literature has emphasised the significance of measuring TikTok use and implications of the user for usage, and vice versa. For example, active and passive SMU has been frequently mentioned in social media research (Gerson et al., 2017; Ozimek et al., 2023; Pagani et al., 2011). According to Verduyn et al. (2021), active SMU, such as sharing thoughts and opinions online, is more beneficial for users than passive SMU because actively engaging with other users has been found to improve mental health through establishing supportive relationships and increasing feelings of social connectedness (Shao, 2009). After engaging in similar behaviour on TikTok, it has been found that user satisfaction, self-validation, and sense of belonging significantly increased (Brammer et al., 2023; Sharabati et al., 2022). Another example during the COVID-19 pandemic was encouraging users to participate in viral trends and challenges to create a sense of social connection and togetherness during periods of physical isolation (Griffiths, 2023; Karhu et al., 2021). However, SMU has been argued to be mostly passive (Pempek et al., 2009), which could also apply to TikTok. An example of this in current research is passively scrolling with associations to boredom, distracting oneself, procrastinating or coping with social isolation during and after the pandemic (Almoallim & Sas, 2023; Marek, 2023; Roberts & David, 2022; Schellewald, 2021). However, different forms of SMU, such as active or passive usage, may appear differently across platforms, with some engaging in more passive usage on some SMP but not others (Jungselius & Weilenmann, 2018). It is also important to consider other SMP and how some pre-existing measures may require alteration in order to accurately reflect the features of that platform, its sample demographics, or motivations behind use (Huang, 2019; Junco, 2013; Sigerson & Cheng, 2018).

2.4.1. Self-reporting social media use

Regarding uncertainty on measuring SMU, various measures already exist in social media research, either adapted from previous measures (e.g. Piwek & Joinson, 2016) or designed from scratch (e.g. Romero-Saletti et al., 2022, 2023), with ongoing debates on validity and whether they are able to measure what they were designed to measure (Flake & Fried, 2020; Verbeij et al., 2021). This has also been present in general technology use, such as smartphones, with researchers arguing that self-reported measures be approached and interpreted with caution (Andrews et al., 2015; Ellis et al., 2019). For example, some measures are dependent on self-reported data, but systematic reviews have found that self-reported usage in comparison to logged SMU data does not accurately reflect SMU, with problematic use scales showing even less accurate associations of SMU when self-reported (Mahalingham et al., 2023; Parry et al., 2021). Respondents in research have also been found to show a tendency to over-report than under-report their smartphone usage (Araujo et al., 2017; McAlaney et al., 2020), which appeared consistent with internet use (Scharkow, 2016) and SMU (Junco, 2013). There have been some occurrences of underestimation also present in self-reporting smartphone use (Muench et al., 2022), but it has been argued that this appears to be less likely with social media (Johannes et al., 2021). Some research has emphasised on how the user's perception of their own usage can become distorted by engaging in self-reported measures, as noted by Lin et al. (2015). Validity concerns have also been raised about scales developed for specific SMP; for example, a study replicating the Facebook Intensity (FBI) scale (Ellison et al., 2007) found that reliability and validity were inferred. However, systematic validation had not been carried out at the time of publication, and there were risks to the scale's validity, such as acquiescence bias (Kuru & Pasek, 2016).

On the other hand, objective methods are less implemented in SMU measures (Griffioen et al., 2020), despite self-reporting measures leading to under- or over-reporting SMU in research (Parry et al., 2021). This seems particularly evident in measures surrounding SMU and well-being. For instance, Sewall et al. (2020) investigated self-reported estimated and "actual" (app-recorded data) use and found that estimated SMU and well-being measures were moderately correlated. However, "actual" SMU showed weak or non-significant associations with well-being, with a discrepancy discovered between estimated and "actual" SMU after further analysis. Boyle et al. (2022) also found under- and overestimation of SMU on multiple SMPs (e.g. Facebook, Instagram, Snapchat, and Twitter), with overestimation of usage more prevalent in females and users engaged in actively using multiple SMPs. Particularly in the context of duration of SMU, incorporating objectively recorded data is also more likely to generate more reliable findings (Alshakhsi et al., 2022). However, it is also unclear as to how duration of usage is defined in research, with most studies showing usage recorded in minutes and hours (Ellis et al., 2019; Wilcockson et al., 2018), yet others express usage as 'screen time' per day, per week, or time from when the device is unlocked and thus active (Felisoni & Godoi, 2018; Rozgonjuk, Levine, et al., 2018). There are also ongoing debates on the appropriateness of using 'screen time' as a measurement of SMU, which Kaye, Orben, et al. (2020) argues has the potential to vary across contexts and over time, resulting in methodological difficulties and the need to investigate varying time periods of SMU (Barry et al., 2024). Thus, there is increasing doubt regarding self-reported measures in social media research and an emphasis on the importance of implementing objective methods to help refine SMU assessment tools (Sewall et al., 2020; Steele et al., 2022).

2.4.2. Misperceptions of social media use

As research continues to strive for reliable means of measuring SMU, it is important to consider the how users may misperceive or inaccurately recall their SMU, and the psychological impact this may have for future research (Yardi-Schoenebeck & Krupka, n.d.). For example, one of the most prevalent misperceptions regarding SMU is underestimating or overestimating the time users spend on SMP (Verbeij et al., 2021). Underestimation when measuring time has also been referred to as downward time distortion, while upward time distortion refers to overestimation (Yang et al., 2024). Sewall et al. (2020) found higher levels of actual SMU were associated with greater inaccuracies of estimated use, with the argument that higher frequency behaviours such as SMU, which is an integrated part of everyday life, would place a cognitive burden on participants to respond accurately. Under- or overestimating SMU could be related to the habitual nature of social media, where short but frequent interactions may accumulate higher usage that goes unnoticed, such as checking notifications or messages (Burnell et al., 2021; Oulasvirta et al., 2011). Prior research has also argued that social media users are expected to experience upward time distortion and perceive that "time flies", thinking they spent longer on social media than they did (Turel & Cavagnaro, 2018), which has also proven to be the case with short-form video SMP like TikTok (Yang et al., 2024). However, Yang et al. (2024) went on to say that students who watch short-form video content on platforms such as TikTok, they were aware that they spent too much time on the app, but experiences of flow states and habitual use led to a loss of time control. However, while using objective measures to obtain accurate SMU is considered a more reliable tool (Alshakhsi et al., 2022). Employing only these measures to see how much time an individual spends on social media may not fully capture their SMU, such as users' thoughts, feelings, or behaviour (Ellis et al., 2019; Mahalingham et al., 2023).

Another common misperception of SMU is the overestimation of one's ability to multitask with multiple devices or apps simultaneously, also referred to as media multitasking (Carrier et al., 2009). This tendency was observed in a study by Brasel and Gips (2011), who also suggested that individuals have a lesser ability to recall their "moment-to-moment" visual attention when engaging in media multitasking. Also, Bowman et al. (2010) found that students, while reading academic resources and texting, overestimated their ability to multitask correctly, which significantly affected their academic performance (Lau, 2017; Mekler, 2021). Furthermore, social media users may also experience digital fatigue from social media overuse, which impact on their well-being (Appel et al., 2019). Research has argued that using digital technology is so integrated into everyday life, it acts as a cognitive offloading resource which lessens fatigue (Nijssen et al., 2018; Risko & Gilbert, 2016; Storm et al., 2016). As result, social media users have been found to experience a greater loss of time due to excessive SMU, leading to increase feelings of digital fatigue or social media fatigue (Zhang et al., 2020). Also, social media users may feel overloaded if confronted with too much information, which has also been argued to lead to perceived fatigue (Sweller, 2011). In the context of social media, users need to constantly process large amounts of information at a rapid pace (Zheng & Ling, 2021). It has been argued that social media users are more likely to experience information overload or other types of overload, such as social overload (Fu et al., 2020). Coupled with compulsive SMU with platforms in which the user is more competent or familiar, they are more likely to be unaware of the time they spent on social media and increase chances of experiencing fatigue (Bright et al., 2015; Wang & Scherr, 2021).

2.4.3. Distributing social media use measures

Furthermore, the manner through which these SMU measures are distributed can also have an impact on the effectiveness of the study. For example, conducting surveys online can be advantageous, particularly for novice researchers, as they are both time- and cost-effective (Wald et al., 2019). This is especially true if it is difficult for the researcher to travel or recruit participants face-to-face because of geographical differences (Fricker & Schonlau, 2002). Evidence also suggests data collected online has improved reliability as opposed to face-to-face surveying (Liu & Wang, 2015). For instance, using an online system to distribute the survey can improve on other elements in online data collection, such as preventing incomplete responses, reduce data errors or researcher bias, and data validation, which can help to minimise measurement error (Fricker & Schonlau, 2002; Liu & Wang, 2015; Musch & Reips, 2000). Also, as online surveys prove to be more accessible for researchers, they can also be an accessible and convenient mode for participants. For example, participants can complete the study in their own time without being observed, which can improve response quality by reducing social desirability bias (Gnambs & Kaspar, 2016). Also, online formats can be beneficial for those who may experience social anxiety or physical limitations when attending a study in-person, allowing for more comfortable and flexible participation (Kelfve et al., 2020).

To take part in an online survey, participants need the necessary tools and skills in order to respond beyond the requirements to participate in the study itself. Examples include, but are not limited to, having the required device, web browser, software, or technological expertise (Miller et al., 2002). Those who participate on online surveys are more likely to be representative of that population (in this case, social media users) because they have access to what is required to participate, such as a device with an internet connection (Wald et al., 2019). However, it is worth noting that those who have what is needed to participate in online research may be more representative of those younger in age, or of a higher socioeconomic or educational status (Riva & Galimberti, 2001; Riva et al., 2003).

2.5. Current theoretical perspectives of TikTok user motivation

In order to understand TikTok use in more depth, it is necessary to consider which psychological theory is most appropriate for assessing user motivation and its relevance to motivations already identified in current research. Such explanations can also be beneficial to further understanding user engagement, content, and social interactions on TikTok, which can improve psychological approaches to this SMP.

2.5.1. Social capital theory

Firstly, as the acronym suggests, SNS are primarily used for forming social networks, which in turn, increase a user's social capital after increased or frequent usage (Xie, 2014). Social capital theory (SCaT) refers to social interactions or relationships based on trust as resources and the resulting benefits, such as emotional satisfaction, companionship, or professional success (Bourdieu, 1986; Coleman, 1990; Fukuyama, 1999). Social capital is also described in research in having two types of connections: bridging (relationships between individuals who may differ in socioeconomic status or other characteristics; Villalonga-Olives et al., 2016) and bonding (connection between individuals who possess a shared demographic, such as family, relatives, or kinship; Woolcock & Sweetser, 2002). To bring this theory into an online perspective, Faucher (2018) put forth the concept of online social capital, in which traditional social networks obtained through social capital are based within a vast ecosystem of digital networks. In the context of SMP, social capital may be attained through forming relationships with other users by following one another's profiles, which exposes both parties to new content, improved well-being, and opportunities to collaborate (e.g. Facebook; Ellison et al., 2007; Johnston et al., 2013). On TikTok, Yang (2021) found that acquiring information, interpersonal communication, and self-presentation significantly positively correlated with bridging and bonding social capital. Similarly, Scherr and Wang (2021) emphasize that TikTok users often engage in strategic self-presentation through carefully curated content to enhance their visibility and popularity, which in turn fosters connections and contributes to social capital formation. Also, due to TikTok's emphasis on UGC, behaviour which involves direct participation when creating content is encouraged (Omar & Dequan, 2020). This may enable creators to accrue social capital by using features similar to other platforms, such as likes, followers, and comments (Bohn et al., 2014; Shao, 2009). It has been argued TikTok's emphasis on UGC is stronger than other SMPs but has been neglected as an area of research due to the newness of the platform (Ahlse et al., 2020), while other SMPs do rely on UGC to some extent (Crowston &

Fagnot, 2018; Moran et al., 2020; Priporas et al., 2017). Despite this, TikTok is argued to be unique in the app's design to encourage quick and easy content creation (Viñuela, 2022). Unlike YouTube, where creating content typically requires external editing software for higher quality content (Roy & Swargiary, 2024), TikTok offers in-app tools for users to create engaging, authentic or self-expressive content for little to no cost without pre-existing skills or knowledge (Daugherty et al., 2008; Rudnichenko, n.d.; Solà, n.d.)

2.5.2. Self-determination theory

Secondly, Self-determination theory (SDT) aims to explain human motivation to achieve a sense of wellness and thriving, driven by three basic psychological needs: autonomy, competence, and relatedness (Deci & Ryan, 1985; Reis et al., 2000; Ryan & Deci, 2017). Autonomy refers to the desire for the ability to have control over one's behaviour, thus motivating the individual to act according to their best interests (Deci & Ryan, 2000, p.231). According to Wang et al. (2016), in the context of social media, this need is particularly important as users learn to express themselves in a manner of their choosing online without concern or desire for validation from others. In the case of TikTok, this could extend to users who are free to make content without external constraints and engage with whom they choose, view content they enjoy, and follow other users of similar mindsets or interests (Putro & Palupi, 2022). Vallerand and Ratelle (2002) put forth that competence comprises an individual's need to interact with others in order to achieve a desired outcome, which relates to community building and interpersonal communication previously mentioned in SCaT. For example, TikTok enables users to edit and be creative with their content by using filters, music, or video editing to share aspects of themselves or their skills or talents in a way that appeals to other uses of similar interests, for example (Bhandari & Bimo, 2020; Scherr & Wang, 2021). From this, the viewer, who receives the positive feedback from other users, increases their engagement on TikTok and in their chosen communities (Wei, 2024).

Relatedness is described as the desire to establish and maintain mutual care with others (Baumeister & Leary, 2007), which can be taken care of in online communities which provide a positive atmosphere (Zhang et al., 2014). Zhao et al. (2023) found that older social media users' need for relatedness can be supported by younger content creators offering their knowledge and experience, such as sharing cooking videos or fitness coaches sharing advice, contributing a sense of closeness to their online community. While SDT offers insight into how basic psychological needs can be applied and adapted to various contexts, both online and offline, it has been argued that limiting to three basic needs may neglect other psychological needs also significant to explaining SMU (Wei et al., 2021), such as social comparison.

2.5.3. Social comparison theory

Social comparison theory (SCoT) suggests that individuals determine their social or personal worth based on an evaluation of their own traits, abilities, or circumstances compared to others with similar attributes (Festinger, 1954; Suls et al., 2002), with upward or downward social comparisons as the most common types mentioned in research (Guyer & Vaughan-Johnston, 2018). Upward social comparisons occur when an individual compares themselves as less than who they are comparing themselves against, resulting in either feelings of lower self-esteem or the desire for self-enhancement, for instance (Gibbons & Gerrard, 1989; Guyer & Vaughan-Johnston, 2018; Smith, 2000). On the other hand, downward social comparisons comprise when an individual who thinks of themselves more favourably when compared to another they perceive as less fortunate to them, resulting in increased feelings of self-esteem or positive self-presentation (Gibbons & Gerrard, 1989; Guyer & Vaughan-Johnston, 2018; Smith, 2000).

With regards to social media, social comparisons can be applied to users comparing their day-to-day lifestyle. For example, users may compare themselves to content creators or influencers who through creative filming and editing, can idealise everyday activities, potentially distorting their followers' perceptions of what their lives should be like, leading to feelings of inadequacy (Mackson et al., 2019; Qiu, 2024). So, other users are driven to achieve a similar or exceeding level of self-presentation or coolness as those they imitate, increasing their own SMU in the process (Arriagada & Ibáñez, 2020; Scherr & Wang, 2021). From this, they are successful in increasing their self-esteem due to upward social comparisons experienced by their followers, and so on (Reade, 2020; Vogel & Rose, 2016). This theory can be applied to TikTok by its algorithm and content recommendations, in which content creators strive to reach as big an audience as possible and seek social validation or positive responses to their content (Andreassen et al., 2017; Scherr & Wang, 2021). While SCoT does offer sufficient explanation for usage in regard to self-presentation, it has been argued that SCoT cannot be the only explanation for the effects of engaging with TikTok content (Joiner et al., 2023). Also, SCoT appears to primarily focus on self-esteem and self-presentation, which, while relevant, are not the only motivations explaining TikTok use identified in research to date.

2.5.4. Uses & gratifications theory

Finally, Uses and gratifications (U&G) theory (Katz et al., 1973; Ruggiero, 2000) appears to be the most prominent theory utilised in research to explain SMU and user motivation. U&G argues that individuals have needs and desires which can be satisfied by engaging with media (Rubin, 2009). A key principle of U&G suggests that an individual's media use is conditional on an awareness of their needs, and the chosen type of media or content depends on psychological, social, or environmental factors (Blumler et al., 1974; Katz et al., 1973). Gratifications are conceptualised as the satisfaction or fulfilment of the user after engaging in their chosen behaviour or viewing their chosen content on their desired platform (Palmgreen, 1984; Papacharissi & Rubin, 2000). U&G has been applied to new forms of technology-mediated communication through SMP, such as Facebook (Quan-Haase & Young, 2010), Instagram (Huang & Su, 2018), Snapchat (Vaterlaus et al., 2016), and Twitter (Chen, 2011).

There are a variety of reasons why people want to engage on social media, and Ellis (2023) argues that people engage on specific platforms based on the type of content they want to see, the identity they wish to present, and the relationships they are looking to form. Therefore, U&G theory also has the potential to incorporate motivations for SMU previously mentioned in SCaT (Yang, 2021), self-determination theory (Wei, 2024), and SCoT (Mackson et al., 2019). In order to maintain research surrounding newer SMPs such as TikTok, the U&G approach needed to be expanded to identify different forms of usage and user behaviour specific to individual platforms (Alhabash & Ma, 2017; Yaqi et al., 2021). To better understand TikTok users, new gratifications have been brought to light specifically relevant to TikTok, such as a desire for fame (Batool, 2021), self-presentation (Scherr & Wang, 2021), information seeking (Falgoust et al., 2022), community building (Cleofas et al., 2022), self-expression (Shao & Lee, 2020), entertainment (Bossen & Kottasz, 2020), and escapism (Vaterlaus & Winter, 2021; Scherr & Wang, 2021). While other theories previously mentioned provide insight into motivations behind TikTok use, fewer motivations are focused upon, such as SCaT and SDT focusing solely on community building (Yang, 2021; Zhang et al., 2014), and SCoT on self-presentation (Guyer & Vaughan-Johnston, 2018). U&G theory provides a more complex and broader overview in multiple explanations underlying SMU (Dolan et al., 2016) which can be applied to explain the same with TikTok usage. Therefore, with this theoretical framework in mind, this study will focus on motivation for TikTok use, focusing on U&G theory.

Current literature also appears to focus on adolescents or students (Alhabash & Ma, 2017; Cleofas et al., 2022; Kircaburun et al., 2020). While these groups are relevant to TikTok's majority user population, there is a need to include the wider TikTok population. Investigating TikTok users such as non-students over 18 or users above the average university or college age may broaden sampling in this field to improve generalisability (Deng et al., 2023; Gallander Wintre et al., 2001). It may also be prudent to consider the quantity of current TikTok research supported with Asian-based samples (Dong & Xie, 2023; Meng & Leung, 2021; Scherr & Wang, 2021; Su et al., 2021; Yao et al., 2023). Before being marketed to the rest of the world, TikTok was originally released to countries in Asia outside of China (Stokel-Walker, 2023), such as Pakistan (Batool, 2021), the Philippines (Cleofas et al., 2022), Indonesia (Putro & Palupi, 2022), and Thailand (Wuttaphan, 2022). Also, with a steady increase in European studies being carried out (Bossen & Kottasz, 2020; Dias & Duarte, 2022; Günlü et al., 2023; Şot, 2022), comparing TikTok usage in Western countries, such as the United Kingdom (UK) and United States (USA), to past research could reveal unexplored cultural similarities or differences as TikTok evolves over time (Coolican, 2024, p.257; Scherr & Wang, 2021).

2.5.5. Summary of theoretical perspectives

Current theoretical perspectives offer insightful frameworks which can be applied to understanding TikTok user motivation with similarities between theories (Andreassen et al., 2017; Wei, 2024; Yang, 2021; Yaqi et al., 2021). However, each theory also shows differences and limitations, highlighting the need for further investigation into the unique elements of the TikTok platform. SCaT emphasises the benefits of social interactions and established relationships, while SDT focuses on satisfying individual psychological needs (Deci & Ryan, 2000; Tsai & Ghoshal, 1998). Both theories appear to emphasise the importance of social interactions and forming communities in online environments, but from different perspectives: SCaT from a social capital perspective, and SDT from the perspective of intrinsic motivation. SCoT describes how individuals assess their worth by comparing themselves to those in a better or lesser position than themselves, which can lead to the desire for self-enhancement or improved self-esteem, respectively (Smith, 2000). In comparison to SCaT, which typically focuses on the benefits of social interactions, SCoT examines how positive or negative impacts of comparisons on social media can occur (Guyer & Vaughan-Johnston, 2018; Yang, 2021). SCoT also differs from SDT in the psychological aspects of SMU, in which SDT focuses on the needs and motivations of online interactions (Wei et al., 2021). In contrast, SCoT focuses on the psychological consequences of comparisons from online interactions (Verduyn et al., 2020). Finally, U&G theory encompasses a more holistic view, with elements from all the previous theories. As various social and psychological factors influence motivations, U&G theory poses the most comprehensive framework for investigating and furthering our understanding of TikTok usage (Dolan et al., 2016).

To summarise each theory's limitations, SCaT does not appear to fully address individual psychological needs or the significance of social comparisons, unlike SDT and SCoT, respectively (Ryan & Deci, 2017; Suls et al., 2002). SDT seems to restrict explanations of user motivation to three basic needs, which SCaT and SCoT both expand upon (Wei et al., 2021). SCoT primarily focuses on self-esteem and self-presentation and does not address other motivations which may be significant, such as community building and entertainment (Joiner et al., 2023). Therefore, by incorporating the most appropriate theory, U&G, research into more recent and under-researched SMP such as TikTok, should consider demographic differences, such as age or culture, and delve into other motivations which may not be identified in other platforms due to the uniqueness of TikTok (Deng et al., 2023; Scherr & Wang, 2021; Yaqi et al., 2021).

2.6. Personality and TikTok use

In addition to explaining SMU and its applicability to various cultures, U&G theory also emphasises the role of personality traits in understanding social media users and their motivations (Kircaburun et al., 2020; Kircaburun & Griffiths, 2018; Omar & Dequan, 2020). Allport (1937) asserted that a person's personality comprises a variety of traits, each of which reflects fundamental characteristics and behaviours that set people apart. It has also been argued that that personality traits are significant predictors of human behaviour and are more likely to portray a person's needs and motives (Landers & Lounsbury, 2006; Woszczynski et al., 2002). Cattell (1948) extracted 16 basic traits from factor analysis of human behaviour to further our understanding of individual personality traits and behavioural responses, resulting in the “16 personality factors test” model. As trait psychologists have replicated and altered Cattell’s original model, the most representative and validated personality assessment model became the Five-Factor Model of personality, also known as the “Big Five” (Goldberg, 1990, 1993; McCrae & Costa, 1987; McCrae & John, 1992). This model comprises five broad personality traits: openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism (acronym OCEAN). An advantage of the Big Five in research is that they reflect how individuals score somewhere in each dimension (Diener & Lucas, 2024). For example, if two people are described as introverts, this does not mean they are the same; they can score somewhere from extremely low or relatively low in extraversion, or anywhere in between (Matthews et al., 2009).

Openness is positively associated with the frequency of SMU and is defined as the tendency to be curious, imaginative, intelligent, or broad-minded (Barrick & Mount, 1991; Zhang et al., 2011). While some research did not find relationships between openness and SMU (Moore & McElroy, 2012), other studies found that those higher in openness were more self-expressive, engaged with other users, and had more online friends (Correa et al., 2010; Lee et al., 2020). However, openness has been argued to be more related to searching behaviour (Wyatt & Phillips, 2005) and appears unlikely to significantly predict SMU (Butt & Phillips, 2008). Nonetheless, if those prone to openness experience higher involvement on social media to share more about themselves and engaging in finding and sharing information (Hughes et al., 2012), this may be relevant to TikTok due to its editing features and various video functions which encourage informative self-expression (Krisadhi et al., 2023; Qiu et al., 2015). In sum, openness may also not be as strong a predictor as it may have been during the COVID-19 pandemic, when engaging with other users directly on SMP, such as TikTok, was more frequent (Krisadhi et al., 2023).

Conscientiousness describes individuals who tend to be organised, goal-oriented and have higher levels of self-control (Anastasi & Urbina, 1997; Roberts et al., 2009). Previous findings have shown that people with higher levels of conscientiousness were typically more cautious and self-aware of how they presented themselves online, typically by posting less content and using social media less frequently (Krisadhi et al., 2023; Marengo et al., 2020; Ryan & Xenos, 2011; Seidman, 2013). Based on these past findings, highly conscientious TikTok users are expected to spend less time online posting content; conscientious users may potentially passively watch others' content as they may not feel the desire to participate in trends, distract themselves or procrastinate (Alan & Kabadayı, 2016; Da-yong & Zhan, 2022).

Extraverted people are typically talkative, sociable, and cheerful (Watson & Clark, 1997). As a result, they use social media more often as a means to socialise with higher numbers of online friends, post more content, or spend time on social media more frequently (Amichai-Hamburger & Vinitzky, 2010; Bowden-Green et al., 2020; Gosling et al., 2011; Ryan & Xenos, 2011). However, Philip and Zakkariya (2016) argued that introverted social media users tend to have increased SMU and show more of their real selves online due to online disinhibition (D'Agata & Kwantes, 2020; Suler, 2004). Therefore, in the case of TikTok, it appears likely that either extroverted or introverted individuals would be more active on TikTok (Blackwell et al., 2017). This could be for various reasons, such as to express themselves by posting more frequently, share their thoughts or opinions, or participate in viral trends or challenges (Amichai-Hamburger et al., 2002; Da-yong & Zhan, 2022; Krisadhi et al., 2023).

People high in *agreeableness* are described as helpful, tolerant, and friendly (Graziano & Eisenberg, 1997). While some research did not find direct links between agreeableness and SMU (Ross et al., 2009), some past findings associated agreeableness with online behaviours similar to gaining a sense of belonging (Seidman, 2013). For example, those high in agreeableness tended to engage in more supportive behaviours, such as engaging with other users' content by giving likes or leaving comments (Moore & McElroy, 2012; Wang et al., 2012) or connect and collaborate with others personally or professionally (Marino et al., 2016; Marshall et al., 2015). As TikTok encourages engagement with fellow users through likes, comments, or saving content, those high in agreeableness appear likely to also use TikTok more frequently (Choi et al., 2017).

Neuroticism is classified as having low levels of emotional stability, high levels of anxiety, and greater sensitivity to threat (Widiger, 2009). Neurotic individuals tend to increase their SMU to seek support or disclose personal problems, which they may struggle with or lack offline (Correa et al., 2010; Hughes et al., 2012; Ross et al., 2009). Other research suggests that neurotic individuals are motivated to engage on social media as a non-threatening environment to receive assurance (Amichai-Hamburger & Vinitzky, 2010; Krisadhi et al., 2023). With this in mind, social media users may be particularly high in neuroticism, or high scores of neuroticism will predict an increase in usage or experience excessive or addictive SMU (Blackwell et al., 2017; Marino et al., 2016; Ponce, 2023). For TikTok users who may be high in neuroticism, the app appears to provide a safe space for its users to find those in a similar situation or of a similar mindset and better express themselves than they would offline (Da-yong & Zhan, 2022; Krisadhi et al., 2023; Şot, 2022).

2.7. Demographic differences in TikTok use

As personality portrays its significance as unique but insightful in social media research, various individual differences such as age, gender, or culture can play a part in explaining TikTok user motivation. Firstly, TikTok appears to possess a higher level of popularity among younger age groups, as previously stated by Ceci (2023b). Younger generations, such as Generation Z (or Gen Z; Dimock, 2019), are well known for their increased amount of time spent on social media (Huang & Su, 2018), and this has been found in various SMP. Individuals who are considered Gen Z are born between 1997 and 2012 (Dimock, 2019) and would be between 13 to 28 years old at the time of writing. For example, Masciantonio & Bourguignon (2023) found that

Snapchat usage was associated with age; the younger the individual was, the more likely they were to use it. This was also the case with Instagram and Facebook (Laor, 2022; Ozimek & Bierhoff, 2016). However, not all prior research appears consistent with these findings, and it has been argued that social media users are not limited to younger age groups (Cotten et al., 2023; Quinn, 2018). For example, individuals aged between 45 and 55 appear to use Facebook more than Twitter or Instagram (Singh et al., 2019) to maintain social connectedness, especially when faced with mobility imitations or when physical connectedness was not possible (Bell et al., 2013). The literature surrounding newer platforms such as Snapchat gave contrasting arguments, with Twitter and Instagram used by both younger and older people (Blank & Lutz, 2017). Regarding TikTok, while most users are considered to be young, but findings from the Pew Research Centre (Eddy, 2024) showed 26% of those aged 50 to 64 and 10% of those 65 and older also use TikTok (Auxier & Anderson, 2021; Qiu, 2022) and so multiple age groups should be investigated in future research (Chao et al., 2023). Different motivations for TikTok use predicted by age also suggest that younger users may engage with TikTok to be more self-expressive than older users, desiring positive feedback (Dhir et al., 2016; Scherr & Wang, 2021). Furthermore, the conceptualisation of age in generations has been used considerably in social media research. For example, some have argued the presence of generational differences in SMU between "social media natives", such as Millennials or Gen Z, or those who adopted social media later in life, also referred to as later generations such as Gen X (Bowe & Wohn, 2015). Differences have also been found in TikTok use, with varying motivations influencing TikTok use frequency between Gen Z and Millennials (also referred to as Generation Y; Borges, 2023).

As the typical age of a TikTok user falls under Gen Z (born 1997 to 2012; Dimock, 2019) or Generation Alpha (born 2010 to 2024; Jha, 2020), research has also emphasised on students being more active on social media than non-students (Nagel et al., 2018). Students, similar to younger users, also have been found to overestimate than underestimate their usage (Boyle et al., 2022) or perceive themselves as addicted to social media (Allahverdi, 2022). Regarding students' gender, female students have been found to use social media significantly more than male students (Boyle et al., 2022; Çömlekçi & Başol, 2019; Kay et al., 2017; Kircaburun et al., 2020; Stefanone et al., 2011), but other studies such as Bashir et al. (2021) found that male students used social media more frequently. It has also been argued that gender influences participation in research, with females more likely to contribute than males (Smith, 2008). However, while females may contribute more than males, the previously mentioned studies do acknowledge some inconsistencies between gender and the accuracy of self-reporting SMU. Çömlekçi and Başol (2019) and Kircaburun et al, (2020) discussed that varying motives for SMU between genders, such as self-presentation and social connection for females and entertainment or information-seeking for males, could explain inconsistencies in usage patterns. Bashir et al. (2021) highlighted how gender norms and societal expectations may affect actual SMU behaviour and self-reporting, contributing to inconsistent findings. Lastly Boyle et al. (2022) noted that the number of platforms used by females was linked to greater reporting inaccuracies, significantly with Instagram and Snapchat.

In contrast, as noted in previous studies regarding problematic, addictive, or day-to-day SMU, there are many studies which focus on students (e.g., Kircaburun et al., 2020). It has been argued that recruiting university students in studies may make results less reliable, such as using course credit to make participation mandatory, and limiting generalisability to other populations (Leentjens & Levenson, 2013; Lewin et al., 2022). While these studies that comprise of student sample can be criticised for their generalisability, students remain a relevant group of interest in research on SMP such as TikTok. University students, or those of a similar age group, have been found to be frequent TikTok users. In the USA, nearly half (47%) of undergraduate students reported they used TikTok daily (Intelligent, 2024), and 62% of those aged 18-29, regardless of their educational background, also say they use TikTok (Gottfried, 2024). With this in mind, recruiting university students allows access to a group that may already be immersed in and could be impacted by TikTok. Also, understanding this group's engagement with TikTok can offer a valuable perspective through which to explore usage patterns and motivations. While this may limit broader generalisability, including university students or those of a similar age as well as other users of various ages would allow for further comparative insight across age groups or other demographics.

On the other hand, some studies also consider social media users without eligibility restrictions, such as student status. For example, some studies placed greater emphasis on the influence of gender in SMU. Laor (2022) found that women use Facebook and Instagram more often than men, which has been supported in other studies (McAndrew & Jeong, 2012; Scott et al., 2017; Sheldon & Bryant, 2016). However, it has been found that men use Twitter and YouTube more often than women (Kircaburun et al., 2020; Laor, 2022). In the case of TikTok, there seems to be an almost even balance of males and females engaging with the app, with approximately 54% of global TikTok users being male as of 2024 (Ceci, 2024b). However, male and female users may be motivated to use SMP, such as TikTok, based on user motivation and the content they wish to see. For instance, females tend to use social media for community building, establishing relationships, or social recognition (Alruwaili, 2017; Cleofas et al., 2022; West et al., 2015). Regarding content, women tend to engage with content that promotes relatability, with other female users posting about their hobbies or lifestyles, offer advice, or engaging in viral trends or challenges (Vaterlaus & Winter, 2021). Male users, on the other hand, are typically drawn to social media for meeting new people and entertainment, seeking out content related to trends or humour (Kircaburun et al., 2020; Vaterlaus & Winter, 2021).

Finally, just as men and women display varying motivations for SMU, so do individuals from different cultural backgrounds, which reflects the way people engage with social media around the world (Guftométros & Guerreiro, 2021). Culture determines how we perceive ourselves and others, how we relate to one another, and how we communicate our ideals and values (Gudykunst & Nishida, 1986; Triandis, 1999). Regarding social media and culture, it has been argued that cultural differences can be expressed through SMU (Kıran & Demirçeviren, 2021), with some studies suggesting that differences exist in SMU between those from individualistic and collectivists cultures (Cho, 2010; Kim et al., 2011). Collectivist cultures are characterised by family or group integrity, membership, and solidarity, emphasizing on the significance of interdependence (Lu & Wan, 2018; Triandis, 1995). In contrast, individualistic cultures focus on uniqueness, personal achievement, and independence (Grossmann & Santos, 2020; Triandis, 1995). However, while individualistic or collectivist cultures may be shared across a single culture, Matsumoto et al. (1996) argued that they can vary between individuals.

Regarding content preferences between cultures on TikTok, Deng et al. (2023) suggested that users from individualistic cultures (such as the USA) use TikTok as a means to escape real-life challenges, self-expression, and for information seeking more than collectivist cultures. Users from collectivist cultures tend to have more prolonged interactions with smaller groups of online friends or followers than those from individualistic cultures, who prefer larger friend groups (Dotan & Zaphiris, 2010; Marcus & Krishnamurthi, 2009). Fortunately, some studies have investigated cross-cultural differences in TikTok use (Scherr & Wang, 2021; Yang, 2022) and exploring engagement on TikTok from the perspective of personality and U&G (Falgoust et al., 2022; Omar and Dequan, 2020). These studies found that TikTok use is driven by trendiness, (Scherr & Wang, 2021), Chinese users are more likely than USA users to be persuaded by influencers to purchase products (Li et al., 2019), and escapism is a significant predictor of TikTok usage and more prevalent in women (Scherr & Wang, 2021). However, some studies tend to focus on young adults, students, or adolescents (Deng et al., 2023; Kıran & Demirçeviren, 2021). Given the highlighted differences between individualistic and collectivist cultures, it would be pertinent to explore usage between two cultures which are considered culturally similar but still possess distinct differences. For example, the UK and USA are both considered individualistic cultures (Hofstede, 1991, 2001) and ease of technological access provides a common ground for comparison (Aalberg et al., 2012). UK students visiting the USA have been found to perceive cultural differences as more prominent (Lyons & Branston, 2006), but current research appears to solely focus on political and information seeking motives in SMU and argued to be similar to traditional media between these cultures (Aalberg et al., 2012; Saldaña et al., 2015).

Therefore, it seems prevalent to investigate potential for other cultural differences between the UK and USA in TikTok use, particularly taking into account TikTok's increase in popularity during and after the COVID-19 pandemic (Feldkamp, 2021). For example, according to the Country comparison tool based on Hofstede's 6-D model (Hofstede, 2001; The Culture Factor Group, 2025), the UK score for individualism is slightly higher than the USA (76 vs 60). This could suggest that UK TikTok users prefer content that is more unique and original as opposed to following trends. On the other hand, the USA and UK show similar scores for indulgence (69 vs 68). This could suggest both cultures like to engage with a mix of TikTok content that comprises serious topics, such as mental or physical health, and more leisurely topics, such as dance, cooking, or comedy. This link suggesting individualistic cultures lean towards more self-expressive content is also supported by Deng et al. (2023). They found, when comparing users from the USA against Chile and Spain, that users from Chile and Spain, which are considered collectivistic societies, perceived TikTok as a tool for socialisation, had more followers, spent less time on the platform, and tend to avoid self-expression. On the other hand, USA users tend to view TikTok less as a socialisation tool and more as a leisure space or as a way to escape.

2.8. Rationale, research questions and hypotheses

As discussed in Chapter 1, there has been growing concern about the impact of TikTok use as problematic or addictive, with less emphasis on a neutral perspective or everyday usage

(Cash et al., 2012; Xu, Tedrick, et al., 2023). With TikTok's presence expanding from East Asia to the rest of the world further investigation is needed into populations beyond students. While TikTok is significantly popular amongst young people, such as students (Alhabash & Ma, 2017; Deng et al., 2023), individuals not in education or of an older age group also engage in frequent TikTok use for similar or different purposes (Cotten et al., 2023; Ng & Indran, 2023). Some studies have suggested that social media use is associated with individuals high in extraversion and neuroticism (Da-yong & Zhan, 2022; Krisadhi et al., 2023; Şot, 2022) and therefore can be applied to TikTok. However, contrasting evidence surrounding introversion and openness, for example (Hughes et al., 2012; Philip and Zakkariya, 2016; Qiu et al., 2015), suggests further investigation into personality and individual social media apps, such as TikTok, is needed. Despite these mixed findings, there is a need for further research in this area, as TikTok continues to gain popularity within the Western world following the COVID-19 pandemic, particularly in the UK and USA (Feldkamp, 2021).

Furthermore, gratifications appropriate to TikTok have also been uncovered in recent years, with a stronger focus on escapism or self-presentation (Brailovskaia et al., 2020; Falgoust et al., 2022; Omar & Dequan, 2020). However, newly established measures must be replicated to assess their validity and replicability to TikTok and its users, particularly when considering self-estimated or objective measures of recording usage (Griffioen et al., 2020; Scherr & Wang, 2021; Syrjälä, 2024). The present study investigated the relationship between demographic factors, personality traits, motives for using TikTok, and everyday TikTok usage in a sample of students and the general public from both countries. This study also aimed to utilise subjective and objectively methods of recording TikTok use with the following research questions and hypotheses:

RQ1: How does self-reported TikTok use compare to in-app recorded use?

H1: There will be a significant difference between the number of hours users self-report spending on TikTok compared to in-app data.

H2: There will be a significant difference between the number of times users self-report opening TikTok compared to in-app data.

RQ2: To what extent does TikTok use vary by demographic factors, personality traits, and user motivation in a UK and USA sample?

H3: Demographic factors (age, gender, and nationality) will significantly predict TikTok use.

H3a: Younger users will show significantly higher levels of actual TikTok use than older users.

H3b: Female users will show significantly higher levels of actual TikTok use than male users.

H3c: There will be significant difference in actual TikTok use between UK and USA users.

H4: Personality traits (extraversion, openness, neuroticism, agreeableness and conscientiousness) will significantly predict TikTok use.

H4a: Higher scores in extraversion, openness, neuroticism will significantly predict higher TikTok use.

H4b: Higher scores in agreeableness and conscientiousness will significantly predict lower TikTok use.

H5: Higher scores of motives for TikTok use (socially rewarding self-presentation, trendiness, escapist addiction, novelty) will significantly predict higher levels of TikTok use.

3. Method

3.1. Design

This study used an overall mixed design, employing between-groups, within-subjects and correlational elements within a single research framework. The between-groups design was used to analyse differences between demographic factors and TikTok use. The within-subjects design was used to compare users' self-reported and in-app recorded TikTok use. Lastly, the correlational design involved multiple regression analyses to identify the extent to which demographic factors, personality traits and motives for use predicted TikTok use. All participants answered all questions in an online survey and all predictor variables were included in each model. Predictor variables for demographic factors were age (in years), gender (male or female), and nationality (UK or USA). Predictor variables for personality were the Big Five personality traits conceptualised from the Big Five (Goldberg, 1990, 1993): openness, conscientiousness, agreeableness, extraversion, and neuroticism. Finally, predictor variables for motives behind TikTok use were dimensions extracted from a survey conducted by Scherr and Wang (2021): socially rewarding self-presentation, novelty, trendiness, and escapist addiction. TikTok usage was recorded in hours and minutes spent on the app and by the number of times it was opened.

There were six outcome variables in this study, each of which were derived from self-reported TikTok use based on app-recorded data. Each outcome variable was analyses in a separate regression model, encompassing six models. These outcome variables are as follows:

- The number of hours spent on TikTok during day-time in the past week. Day-time was conceptualised according to TikTok's usage settings as 6am to 10pm.
- The number of hours spent on TikTok during night-time in the past week. Night-time was conceptualised according to TikTok's usage settings as 10pm to 6am.

- The total number of hours spent on TikTok in the past week. This was conceptualised as a combined total of day-time and night-time usage.
- The number of times users opened TikTok during day-time in the past week. This was conceptualised according to TikTok's usage settings as from 6am to 10pm.
- The number of times users opened TikTok during night-time in the past week. This was also conceptualised according to TikTok's settings as 10pm to 6am.
- The total number of times users opened TikTok in the past week. This was conceptualised as a combined total of day-time and night-time.

3.2. Participants

A priori power analysis was conducted using G*Power version 3.1.9.7 (Faul et al., 2007) to determine the minimum sample size required to test the study's hypotheses. Results from Scherr and Wang (2021) indicated the required sample size to achieve 80% power for detecting a medium effect ($0.3 \leq d \leq 0.5$; Cohen, 2013), at a significance criterion of $\alpha = .05$, was $N = 84$ for correlations between predictors and $N = 84$ for hierarchical regression analysis. Accounting for a potential attrition rate of 20% based on previous research (Scherr & Wang, 2021), an additional 32 participants were recruited. Thus, the obtained sample size of $N = 361$ is more than adequate for this study based on the power analysis concluding a sample size of $N \geq 116$.

Participants were recruited using convenience and purposive sampling techniques. The study was advertised to first- and second-year undergraduate psychology students at Bournemouth University through Sona Systems (2025), an online research participation recruitment system. The study was also advertised to the general public on Prolific (2025), an online study recruitment platform. Inclusion criteria required all participants to be of UK or USA nationality, aged 18 or older, fluent in English, and an active user of TikTok. An active user was defined as having accessed TikTok in the past 30 days. As compensation for participating, BU students were awarded 0.25 course credits through Sona Systems, and participants recruited through Prolific received £1.50 or United States dollar (USD) equivalent for their participation.

This study aimed to specifically examine the demographics of TikTok users in the UK and USA, acknowledging the difficulty in accurately determining the quantity of participants of either nationality. To attempt to overcome sampling bias, a benefit of an online survey via Prolific was that the survey could be accessible and accommodate individuals living in different time zones. To prevent negligent completion, compensation was offered on Sona and Prolific.

A total of 361 participants completed the survey, ranging from 18 to 68 years (M = 28.72, SD = 10.42). Descriptive statistics of participants are shown in Table 2. While incorporating a more diverse cross-cultural sample could prove insightful for this research question, recruiting participants from English-speaking countries, such as the UK and USA, allows for improved generalisability or improved validity due to no risk of misinterpretation of responses in the survey because of mistranslation (Laajaj et al., 2019).

Table 2.

Descriptive statistics of participant demographics.

	UK		USA	
Variables	**n (261)**	**%**	**n (100)**	**%**
Gender				
Female	198	75.9	72	72.0
Male	63	24.1	28	28.0
Age Category				
Younger users (18-34 years)	199	76.2	67	67.0
Older users (35+ years)	62	23.8	33	33.0
Education Level				
Less than A-level or High School Diploma	12	4.6	0	0.0
A-Level or High School Diploma	141	54.0	22	22.0
Associates Degree	6	2.3	10	10.0
Bachelor's Degree	72	27.6	56	56.0
Master's Degree	24	9.2	11	11.0
Professional Degree	3	1.1	1	1.0
Doctorate Degree	1	0.4	0	0.0
Did not disclose	2	0.8	0	0.0
Employment Status				
Employed full-time	93	35.6	58	58.0
Employed part-time	25	9.6	16	16.0
Unemployed	10	3.8	12	12.0
Retired	1	0.4	1	1.0
Student	118	45.2	7	7.0
Self-employed or Freelance	11	4.2	6	6.0
Did not disclose	3	1.1	0	0.0

Notes: N = 361.

3.3. Materials

3.3.1. Demographic factors

Participants self-reported their gender (male, female, non-binary, gender neutral, third gender, or other), age in years, nationality (UK or USA), most recently completed or highest level of education, and current employment status (if two or more statuses applied to them, such as a full-time student who also has a part-time job, they were instructed to choose the more prominent status). Six participants disclosed their gender as non-binary or gender neutral but were removed from the analysis as analysis for this subgroup with so few participants could lead to unreliable or non-robust results and lack sufficient power for inferential analysis (Cao et al., 2024).

3.3.2. Social media use and TikTok use

Participants self-reported which SMPs they use in addition to TikTok, their TikTok profile status (public or private), how long they have been using TikTok (in years), how many TikTok accounts they follow, how many accounts follow them, the number of profile likes they have, whether they use TikTok for business, and their thoughts on their TikTok usage since the COVID-19 lockdown (if applicable).

3.3.3. Self-estimated and actual TikTok day-/night-time use

Participants self-estimated how often they used TikTok (in hours) and how many times they opened the app in the past week. With instructions to find their usage data in the 'Settings and privacy' section of the TikTok app, participants then reported their recorded usage from the past week in the day-time and at night-time. According to the TikTok app, day-time is recorded from 6am to 10pm, and night-time from 10pm to 6am. This method was more suitable for reporting TikTok use as externally recorded usage data in the app would be more objective and less prone to subjective means of self-reporting usage, such as memory bias (Yao et al., 2023).

3.3.4. Big Five Inventory-10 (BFI-10)

The study used the Big-Five Inventory-10 (BFI-10; Rammstedt & John, 2007), which asked participants 10 statements to rate how much they agreed or disagreed with how each statement describes their personality. Extracted from the Big Five Inventory-44 (BFI-44; John & Srivastava, 1999), this is one of the most commonly used scales to measure the Big Five personality traits for research, which may not be able to accommodate the BFI-44 (Pejić et al., 2014; Rammstedt et al., 2020). Despite being a compressed version of the original scale, the BFI-10 shows good internal consistency (*r* = 0.83), high re-test reliability (Rammstedt et al., 2012), and satisfactory structural validity in WEIRD countries (Steyn & Ndofirepi, 2022). Cronbach's alpha reliability coefficients for each personality trait were 0.77 for openness, 0.80 for conscientiousness, 0.80 for extraversion, 0.73 for agreeableness, and 0.80 for neuroticism (Husain et al., 2025). Each statement has responses on a Likert (1932) scale, ranging from 1 to 5 (1=disagree strongly, 2=disagree a little, 3=neither agree nor disagree, 4=agree a little, 5=agree strongly). See Table 3 for example statements for each trait.

Table 3.

Example statement for each personality trait, extracted from the Big Five Inventory-10 (BFI-10; Rammstedt & John, 2007).

	Example Statement: *I see myself as someone who…*
Extraversion	…is outgoing, sociable
Agreeableness	…is generally trusting
Conscientiousness	…does a thorough job
Neuroticism	…gets nervous easily
Openness	…has an active imagination

3.3.5. Motives for TikTok Use

The Motives for TikTok Use questionnaire designed by Scherr and Wang (2021) was used to ask participants how likely they are to use TikTok dependent on various motivational factors: socially rewarding self-presentation, trendiness, escapist addiction, and novelty. Based on Scherr and Wang's findings, the reliability of the multiple-item motives were satisfactory (based on Cronbach's alpha ranging from 0.75 – 0.88). This measure was used to build upon their prior findings in China in other countries (p.7) as it has been found to have satisfactory reliability. This measure was also selected because access had been provided to all materials, including an appendix of the questions used, to allow for precise replication in this study. While the measure was originally designed for a Chinese sample, access to comprehensive materials had ensured consistency and comparability applied to this study's UK and USA sample. Each statement began with "I use TikTok (because)…" with responses ranging on a five-point Likert scale (1=totally disagree, 2=disagree a little, 3=neither agree nor disagree, 4=agree a little, 5=totally agree). See Table 4 for an example statement for each motive.

Table 4.

Example statement for each dimension extracted from Motives for TikTok Use (Scherr & Wang, 2021).

	Example Statement: *I use TikTok (because)…*
Socially rewarding self-presentation	…I can get "likes" from others by filming and posting TikTok videos
Trendiness	…everybody else is using it
Escapist addiction	…I can't stop using it
Novelty	…there are many new things on TikTok

3.4. Procedure

Participants volunteered through Sona or Prolific and were presented with a link that redirected them to the survey hosted by Qualtrics (2023). After clicking on the link, they were required to read a participant information sheet (Appendix A), which outlined the purpose of the study, what information would be requested from them and how their data would be used. Participants were then requested to read a consent to participate statement and choose to give or not give consent. Participants who chose not to give consent were taken directly to the end of the survey and thanked for their time. For participants who gave informed consent, they began the survey by answering the demographic information questions. Questions regarding their social media usage followed this, then their self-reported TikTok usage. Counterbalancing was not implemented because participants needed to provide estimates of their TikTok usage before viewing their in-app data. Awareness of their actual usage first could result in anchoring or recall bias and affect the validity of the self-reported data (Althubaiti, 2016; Furnham & Boo, 2011). They were then asked to complete the BFI-10 (Rammstedt & John, 2007), followed by the Motives of TikTok Use questionnaire (Scherr & Wang, 2021).

After completing the survey, participants were given a debrief form and contact details in case of queries or complaints about the study they wished to raise (Appendix C). They were also reminded about support services to contact in case of feelings of discomfort during the survey. Finally, they were thanked for participating and administered their course credit or monetary remuneration. The study took approximately 10 minutes to complete, and the full list of survey questions can be found in Appendix B.

Before commencing data collection, it was necessary to conduct preliminary tests on the survey to ensure the suitability and clarity of the questions, and calculate appropriate compensation based on completion time. This enables the measures used in this study to ensure their usefulness, clarify misunderstandings, and help to inform new researchers, in particular, of the practical applications of pilot testing (Brooks et al., 2016; Ruel et al., 2016). A short pilot test was conducted with the survey reviewed on Qualtrics by two colleagues to ensure the design was effective and there were no technical issues. The survey was estimated at 10 minutes to complete, and so compensation was declared at 0.25 course credits (equivalent to 15 minutes or less of research participation) for participants recruited through Sona. Data collection via Sona Systems commenced on 20th December and concluded on 29th December 2023.

A pilot test on Prolific was conducted from the 30th of January to 2nd of February 2024 with 25 participants to calculate a median time completion rate for the survey and thus ensure accurate compensation was given to comply with Prolific's guidelines of ethical rewards for research participation. After recruiting 25 participants via Prolific with Qualtrics, 15 responses were incomplete and considered invalid. The remaining 10 responses, however, were complete and fully understood by the participants. So, no revisions to the questions were needed, and their responses were also included in the data analysis. On 14th February 2024, the remaining data collection was conducted with appropriate compensation and concluded on 16th February.

3.5. Ethics

Ethical guidance was taken from the British Psychological Society (BPS) Code of Human Research Ethics (2021b), Code of Ethics & Conduct (2021a), and Practice Guidelines (2017). Bournemouth University's (BU) Faculty of Science & Technology Research Ethics Committee granted ethical approval for this study (ID: 52239). The study was classified as low risk, no personal or identifiable information was requested from participants, and deception was not required.

Participants read an information sheet (Appendix A) before proceeding to the survey, describing the information that will be requested of them, how their data will be managed and stored, how their anonymity throughout the study will be maintained, and contact information in case of queries or complaints. Participants provided informed consent by ticking the box which stated, "I have read and understood the Participant Information Sheet and consent to take part in this questionnaire". After the survey, participants were debriefed and given information on the benefits of the study's results, guidance for withdrawal from the study if they wished, and contact details on well-being and mental health services should they require it (Appendix C).

3.6. Data Analysis

Prior to analysis, the collected data was exported from Qualtrics to Microsoft Excel (Microsoft Corporation, 2018) and processed for the removal of outliers or ineligible responses. Scores were calculated for BFI-10 personality trait and Motives for TikTok Use scores; for scoring instructions see Appendices D and E. A total of 426 participants accessed the survey, and 59 were removed if consent was not given, they did not identify as male or female, or the participant did not respond correctly to the survey. For instance, a participant's data was excluded if they gave unquantifiable responses, such as "hundreds" when referring to how many times they opened TikTok, instead of stating a number, such as 100. The final sample comprised 361 (≈85%) eligible participants. The open-source statistics program JASP (version 0.14; 2021) was used to conduct statistical analysis.

Independent samples t-tests were used to identify differences between demographic factors and in-app recorded TikTok use. Correlation analysis was used to identify relationships between predictors and a series of hierarchical regression analyses (Cramer, 2003) were conducted for each of the outcome variables (hours spent on TikTok: day-time; night-time; total; number of times TikTok was opened: day-time; night-time; total). Hierarchical regression analysis was used as it is a more reliable statistical test used in past research as a more suitable approach when comparing personality traits or motivations for use and SMU (Kircaburun et al., 2020; Meng & Leung, 2021; Omar & Dequan, 2020). Due to a lower sample size, other methods such as structural equation modelling (SEM; Giles, 2002) were not appropriate and therefore not used in the analysis.

In the hierarchical regression analyses, demographic variables (age, gender, nationality) were entered in the first block to isolate the effects of individual differences beyond basic demographic factors. Personality traits were in the second block as past research has suggested personality traits are relevant to understanding SMU (Kircaburun et al., 2020; Kircaburun & Griffiths, 2018; Omar & Dequan, 2020) and so their contribution beyond demographic characteristics could be assessed. Motives for TikTok use was in the third block as this allowed the analysis to determine the significance of predictors specific to TikTok itself while aligned with U&G theory. Prior to the analysis, three categorical variables were dummy-coded (Chen, 2022): age, gender and nationality**.** Age was dummy-coded as younger users (aged 18-34 years) equals 1 and older users (35 years and above) equals 0 to align with previous research in which 18-34 year olds were considered a meaningful younger cohort when assessing SMU (Pew Research Center, 2023). Gender was dummy-coded as 1 for female and 0 for male participants. Nationality was dummy-coded as 1 for UK and 0 for USA.

4. Results

4.1. Descriptive Statistics

Of 361 participants, 74.8% were female and 73.7% were categorised as younger TikTok users (18 – 34 years). Participants' most recent or highest level of education from the UK was A-Levels, or equivalent (54.0%), and in the USA was a Bachelor's degree (56.0%). Participants were also of different employment statuses with the majority of UK participants employed full-time (35.6%) or students (45.2%), and USA participants employed full-time (58.0%). Descriptive statistics of the participants are shown in Table 3. All participants also self-reported the use of at least one of the other SMPs shown in Appendix F, with the top three most used platforms being Instagram (N = 327), YouTube (N = 292), and WhatsApp (N = 261).

Participants reported they had been using TikTok for an average of 3 years (28.0%), followed by 2 years and 4 years in the UK (23.0%) and USA (26.0%), respectively. Most participants from the UK disclosed having a private profile (50.6%) while the majority from the USA disclosed having a public profile (58.0%). Most of the sample (87.8%) disclosed possessing only one TikTok profile as opposed to more than one (12.2%). Most of the sample do not use TikTok for business purposes (92.0%) in comparison to those who do (8.0%). When asked about their usage since the COVID-19 pandemic, most participants reported their TikTok usage had increased (61.2%), while 15.6% of participants said their usage decreased and 15.2% said their usage did not change (see Appendix G).

4.1. Inferential Statistics

To control for the increased risk of Type I error associated with multiple comparisons, Bonferroni corrections were applied to all t-tests. With two paired sample t-tests conducted for H1 and H2, the corrected alpha level was set at $\alpha = .025$ (.05/2). With three independent sample t-tests conducted for H3, H4, and H5, the corrected alpha level was set at $\alpha = .017$ (.05/3) Results were interpreted with this adjusted alpha level in mind.

4.2.1 There will be a significant difference between the number of hours users self-report spending on TikTok compared to in-app data (H1)

Participants self-reported they spent an average of 9.97 hours (approximately 9 hours, 58 minutes) on TikTok in the past week. According to in-app data, participants spent an average of 4.98 hours (approximately 4 hours, 58 minutes) on TikTok in the past week. Shapiro-Wilk tests showed that normality cannot be assumed, $W = .77$, $p < .001$. A paired samples student's t-test revealed a significant difference in the number of hours participants estimated they spent on TikTok in the past week compared to in-app data, $t(360) = 10.16$, $p < .001$, $d = .54$, with participants' estimates (M = 9.97, SD = 9.44) significantly higher than in-app recorded data (M = 4.98, SD = 6.81), supporting H1. Complete analysis outputs can be found in Appendix H.

4.2.2. There will be a significant difference between the number of times users self-report opening TikTok compared to in-app data (H2)

Participants self-reported they opened TikTok on an average of 44 times in the past week. According to in-app data, participants opened TikTok on an average of 89 times in the past week. Shapiro-Wilk tests showed that normality cannot be assumed, W = .68, p < .001. A paired samples student's t-test found a significant difference between participants' estimate of the number of times they opened TikTok in the past week compared to in-app data, $t(360)$ = -7.55, p < .001, d = -.40. Participants' estimates (M = 43.94, SD = 91.64) were significantly lower than in-app data (M = 89.44, SD = 98.37), supporting H2. Complete analysis outputs can be found in Appendix I.

4.2.3. Younger users will show significantly higher levels of actual TikTok use than older users (H3a)

For the number of hours spent on TikTok between younger and older users, Shapiro-Wilk tests showed that normality cannot be assumed in the younger users (W = .77, p < .001) and older users (W = .61, p < .001) groups. A Levene's test also showed that equality of variances cannot be assumed, F = 9.03, p = .003. So, to compare both groups, a Welch's t-test was conducted. As shown in Table 5, TikTok use in hours was higher for younger users (M = 5.55, SD = 7.07) than older users (M = 3.38, SD = 5.76). A Welch's t-test confirmed that these differences were statistically significant, $t(201.83)$ = -2.96, p = .003, d = -.34, supporting H3a. For complete analysis outputs, see appendix J.

Table 5.

Independent samples t-test results comparing number of hours spent on TikTok use in the past week, according to demographic factors.

Comparison	M_1 **(**SD_1**)**	M_2 **(**SD_2**)**	$t(df)$	p	**Cohen's** d
Younger vs Older users	5.55 (7.07)	3.38 (5.76)	-2.96 (201.83)	.003	-.34
Female vs Male	5.47 (7.01)	3.50 (5.98)	2.60 (179.81)	.010	.30
UK vs USA	5.95 (7.26)	2.45 (4.62)	5.43 (279.63)	< .001	.12

Note. M = Mean, SD = Standard Deviation. Cohen's d values represent effect sizes (small ≈ 0.2, medium ≈ 0.5, large ≈ 0.8). To implement Bonferroni corrections, the corrected alpha level was set at $\alpha = .017$.

For the number of times TikTok was opened between younger and older users, Shapiro - Wilk tests showed that normality cannot be assumed in the younger (W = .82, p < .001) and older (W = .71, p < .001) groups. Levene's test also showed that equality of variances can be assumed, F = 18.56, p < .001. For this reason, to compare both groups, a Welch's t-test was conducted. As shown in Table 6, the average number of times TikTok was opened by younger users was higher (M = 103.58, SD = 104.50) compared to older users (M = 49.87, SD = 64.26). A Welch's t-test confirmed that these differences were statistically significant, $t(269) = -5.84$, p < .001, d = -.62, also supporting H3a. For complete analysis outputs, see appendix K.

Table 6.

Independent samples t-test results comparing number of times users opened TikTok in the past week, according to demographic factors.

Comparison	***M_1 (SD_1)***	***M_2 (SD_2)***	***t(df)***	***p***	**Cohen's *d***
Younger vs Older Users	103.56 (104.50)	49.87 (64.26)	-5.84 (269)	< .001	-.62
Female vs Male	91.91 (99.05)	82.1 (96.51)	.83 (158.55)	.408	.10
UK vs USA	95.22 (102.89)	74.37 (84.07)	1.98 (217.93)	.049	.22

Note. *M* = Mean, *SD* = Standard Deviation. Cohen's *d* values represent effect sizes (small ≈ 0.2, medium ≈ 0.5, large ≈ 0.8). To implement Bonferroni corrections, the corrected alpha level was set at $\alpha = .017$.

4.2.4. Female users will show significantly higher levels of actual TikTok use than male users (H3b)

For the number of hours spent on TikTok between male and female users, Shapiro-Wilk tests showed that normality cannot be assumed in the male ($W = .62$, $p < .001$) and female ($W = .77$, $p < .001$) groups. Levene's test also showed that equality of variances cannot be assumed, $F = 5.41$, $p = .021$. For this reason, to compare both groups, a Welch's t-test was conducted. As can be seen in Table 4, on average, females' TikTok usage in hours was higher ($M = 5.47$, $SD = 7.01$) compared to males ($M = 3.50$, $SD = 5.98$). A Welch's t-test confirmed that these differences were statistically significant, $t(179.81) = -2.60$, $p = .010$, $d = .30$, supporting H3b. For complete analysis outputs, see appendix L.

For the number of times TikTok was opened between genders, Shapiro-Wilk tests showed that normality cannot be assumed in the male ($W = .80$, $p < .001$) and female ($W = .77$, $p < .001$) groups. Levene's test also showed that equality of variances cannot be assumed, $F < .001$, $p = 1$. For this reason, to compare both groups, a Welch's t-test was conducted. As also shown in Table X, on average, the number of times TikTok was opened by females was higher ($M = 91.91$, *SD* = 99.05) compared to males (*M* = 82.13, *SD* = 96.51). A Welch's t-test confirmed that these differences were not statistically significant, *t*(158.55) = -.83, *p* = .408, *d* = .10, not supporting H3b. For complete analysis outputs, see appendix M.

4.2.5. There will be significant difference in actual TikTok use between UK and USA users (H3c)

For the number of hours spent on TikTok between participants from the UK and USA, Shapiro -Wilk tests showed that normality cannot be assumed in the UK ($W = 0.54$, $p < .001$) and USA ($W = 0.79$, $p < .001$) groups. Levene's test also showed that equality of variances cannot be assumed, $F = 33.90$, $p < .001$. So, to compare both groups, a Welch's t-test was conducted. As shown in Table 4, the average number of hours spent on TikTok by participants from the UK was higher (*M* = 5.95, *SD* = 7.26) compared to participants from the USA (*M* = 2.45, *SD* = 4.62). A Welch's t-test confirmed that these differences were statistically significant, $t(279.63) = -5.43$, $p < .001$, $d = 0.58$, supporting H3c. For complete analysis outputs, see appendix N.

For the number of times TikTok was opened between UK and USA users, Shapiro -Wilk tests showed that normality cannot be assumed in the UK ($W = 0.80$, $p < .001$) and USA ($W = 0.78$, $p < .001$) groups. Levene's test also showed that equality of variances can be assumed, $F = 3.49$, $p = .063$. For this reason, to compare both groups, a student's t-test was conducted. As shown in Table 5, the average number of times TikTok was opened by participants from the UK was higher (*M* = 95.22, *SD* = 102.89) compared to participants from the USA (*M* = 74.37, *SD* = 84.07). An independent samples student's t-test confirmed that these differences were not statistically significant, $t(217.93) = 1.98$, $p = .049$, $d = .22$, so H3c was not supported. For complete analysis outputs, see appendix O.

4.2.6. Analysis of the predictor variables (RQ2, H3-5)

Means, standard deviations, skewness and kurtosis for all predictor and outcome variables are presented in Appendices P and Q, respectively, with minimum and maximum values calculated for the outcome variables. Overall, the skewness and kurtosis values fall between normal ranges for all predictor variables in samples greater than 300, i.e., ±2 for skewness and ±7 for kurtosis (Kim, 2013; Kline, 2023), with a deviation of the skewness of night-time usage in hours (2.26) and number of times opened (3.00), and from kurtosis in night-time number of times opened (12.84). Outliers were tested for by using Cook's Distance to consider the effect of a single case on the model as a whole and values greater than 1 were considered extreme (Cook, 1977; Cook & Weisberg, 1982); however, none were identified. Outliers in BFI-10 scores were all valid cases and so no participants were removed (Orr et al., 1991); this was also the case for Motives for TikTok Use scores.

Upon inspection of variable boxplots and histograms, outliers were identified in the upper quartile of the distributions across all outcome variables and retained for analysis. This method was employed because some argue that discarding outliers assumed as harmful from the analysis is not recommended, particularly if they can be potential points of future inquiry (Mohrman & Lawler, 2012; Osborne & Overbay, 2004; Thériault et al., 2024), also referred to as interesting outliers (Aguinis et al., 2013). Thus, outliers identified under a standardised residual z-score of ±3.29 (Field, 2024) were retained for analysis. To test for multicollinearity, Pearson's correlations were run on all predictors and no multicollinearity was shown (see Appendix R). For all predictors, VIF values were <2 and Tolerance values were >0.5. Independence of predictors was confirmed with the Durbin–Watson value between 1 and 3. Assumptions of normality and homoscedasticity were also met.

4.2.7. Overview of hierarchical regression analysis (RQ2, H3-5)

Within the hierarchical regression analysis, demographic factors (i.e.: age, gender, and nationality) were entered in the first block of the model, followed by personality traits (extraversion, agreeableness, conscientiousness, neuroticism, openness) in the second block and motives for TikTok use (socially rewarding self-presentation, trendiness, escapist addiction, novelty) in the third block. Testing the influence of variables in blocks in a step-by-step process allows the ability to determine how much changes in variance (ΔR^2) were explained by identified variables in each block while controlling for the overlapping effects of other predictor variables. Six separate hierarchical regression analyses were conducted to compare the six outcome variables of TikTok usage: hours spent on TikTok (day-time, night-time, and combined total) and number of times the app was opened (day-time, night-time, and combined total) in the past week. The final hierarchical regression analysis encompasses six models, each with a different single outcome variable.

4.2.8. Hierarchical regression model of predictors with the number of hours spent on TikTok during the day as the outcome variable

For hours spent on TikTok during the day-time, results showed that in the first block analysis, demographic factors significantly contributed to the regression model, $F(3, 357) = 8.82$, $p < .001$, $R^2 = .069$, $R^2_{adjusted} = .061$, and accounted for 6.9% of the variance. Age ($\beta = .11$, $t = 2.12$, $p = .035$), gender ($\beta = .14$, $t = 2.70$, $p = .007$), and nationality ($\beta = .18$, $t = 3.53$, $p < .001$) all positively and significantly predict day-time usage, supporting H3 (Demographic factors (age, gender, and nationality) will significantly predict TikTok use). For complete analysis outputs, see Appendix S.

For the second block analysis, personality traits also contributed significantly to the regression model, $\Delta F(5, 355) = 4.16$, $p = .001$, $R^2 = .055$, $R^2_{adjusted} = .042$, and accounted for 5.5% of the variance. Neuroticism ($\beta = .14$, $t = 2.40$, $p = .017$) positively and significantly predicted day-time usage, while extraversion ($\beta = .09$, $t = 1.59$, $p = .113$) did not significantly predict day-time usage. Openness ($\beta = -.15$, $t = -2.83$, $p = .005$) did not significantly predict day-time usage, partially supporting H4a overall. Agreeableness ($\beta = .10$, $t = 1.90$, $p = .059$) did not significantly predict day-time usage, while conscientiousness ($\beta = -.10$, $t = -1.98$, $p = .048$) negatively and significantly predicted day-time usage, partially supporting H4b. For complete analysis outputs, see Appendix T.

In the final block analysis, motives for TikTok use did not significantly contribute to the regression model, $\Delta F(4, 356) = 2.10$, $p < .08$, $R^2 = .023$, $R^2_{\text{adjusted}} = .012$, and collectively accounted for 2.3% of the variance. Socially rewarding self-presentation ($\beta = .03$, $t = .53$, $p = .593$), trendiness ($\beta = .04$, $t = .57$, $p = .570$), and novelty ($\beta = -.06$, $t = -1.04$, $p = .299$) did not significantly predict day-time usage, so H5 (Higher scores of motives for TikTok use (socially rewarding self-presentation, trendiness, escapist addiction, novelty) will significantly predict higher levels of TikTok use) was not supported. However, escapist addiction ($\beta = .13$, $t = 2.24$, $p = .026$) positively and significantly predicted day-time usage, partially supporting H5 overall. For complete analysis outputs, see Appendix U.

In summary, being young, female, British, more neurotic, less conscientious, less open to experience, and more motivated to escape were associated with higher levels of TikTok usage during the day. Regression coefficients are presented in Table 7.

Table 7.

Hierarchical regression results for the number of hours spent on TikTok in the past week during day-time (6am-10pm).

Predictor	*B*	*SE B*	β	*t*	R^2	ΔR^2
Block 1: Demographic Factors					.069	.055***
Age	0.11	0.52	.11	2.12*		
Gender	0.14	0.53	.14	2.70**		
Nationality	0.18	0.52	.18	3.53***		
Block 2: Personality Traits					.055	.033**
Extraversion	0.20	0.13	.09	1.59		
Agreeableness	0.26	0.13	.10	1.90		
Conscientiousness	-0.29	0.14	-.10	-1.98*		
Neuroticism	0.30	0.12	.14	2.40*		
Openness	-0.38	0.14	-.15	-2.83**		
Block 3: Motives for TikTok Use					.023	.009
Socially rewarding self-presentation	0.02	0.03	.03	.53		
Trendiness	0.06	0.11	.04	.57		
Escapist addiction	0.18	0.08	.13	2.24*		
Novelty	-0.29	0.27	-.06	-1.04		

Notes: N = 361; *p < .05; **p < .01; ***p < .001; 0 = male, 1 = female. 0 = United States of America, 1 = United Kingdom. 0 = older user, 1 = younger user. *SE B* = Standard Error of Beta.

4.2.9. Hierarchical regression model of predictors with the number of hours spent on TikTok at night as the outcome variable

For hours spent on TikTok during night-time, results showed that in the first block, demographic factors contributed significantly to the regression model, $F(3, 357) = 9.04$, p < .001, $R^2 = .071$, $R^2_{adjusted} = .063$, and accounted for 7.1% of the variance. Age (β = .78, $t = 2.26$, $p = .024$) and nationality (β = 1.43, $t = 4.24$, $p < .001$) positively and significantly predicted night-time usage, supporting H3 (Demographic factors (age, gender, and nationality) will significantly predict TikTok use). However, gender (β = .44, $t = 126$, $p = .208$) did not significantly predict night-time usage, partially supporting H3 overall. For complete analysis outputs, see Appendix V.

For the second block analysis, personality traits also contributed significantly to the regression model, $\Delta F(5, 355) = 3.23$, $p = .007$, $R^2 = .044$, $R^2_{\text{adjusted}} = .030$, and accounted for 4.4% of the variance. Extraversion ($\beta = .12$, $t = 2.15$, $p = .032$) positively and significantly predicted night-time usage, supporting H4a (Higher scores in extraversion, openness, neuroticism will significantly predict higher TikTok use), while openness ($\beta = -.14$, $t = -2.65$, $p = .008$) negatively and significantly predicted night-time usage and neuroticism ($\beta = .11$, $t = 1.85$, $p = .065$) did not significantly, predict night-time usage, partially supporting H4a overall. Agreeableness ($\beta = .06$, $t = 1.01$, $p = .313$) and conscientiousness ($\beta = -.09$, $t = -1.71$, $p = .088$) did not significantly predict night-time usage, so H4b (Higher scores in agreeableness and conscientiousness will significantly predict lower TikTok use) was not supported. For complete analysis outputs, see Appendix W.

In the final block analysis, motives for TikTok use did not significantly contribute to the regression model, $\Delta F(4, 356) = .85$, $p = .492$, $R^2 = .010$, $R^2_{\text{adjusted}} = -.002$, and collectively accounted for 1.0% of the variance. Also, none of the individual motives for TikTok use were significant predictors. Socially rewarding self-presentation ($\beta = .06$, $t = 1.00$, $p = .320$), trendiness ($\beta = .008$, $t = .12$, $p = .902$), escapist addiction ($\beta = .07$, $t = 1.15$, $p = .250$) and novelty ($\beta = -.05$, $t = -.91$, $p = .361$) did not significantly predict night-time usage, so H5 (Higher scores of motives for TikTok use (socially rewarding self-presentation, trendiness, escapist addiction, novelty) will significantly predict higher levels of TikTok use) was not supported. For complete analysis outputs, see Appendix X.

In summary, being young, British, less open to experience, and more extraverted were related to higher TikTok usage at night. Regression coefficients are presented in Table 8.

Table 8.

Hierarchical regression model for the number of hours spent on TikTok in the past week during night-time (10pm-6am).

Predictor	*B*	*SE B*	β	*t*	R^2	ΔR^2
Block 1: Demographic Factors					.071	.063***
Age	0.78	0.34	.12	2.26*		
Gender	0.44	0.35	.06	1.26		
Nationality	1.43	0.34	.22	4.24***		
Block 2: Personality Traits					.044	.023**
Extraversion	0.18	0.08	.12	2.15*		
Agreeableness	0.09	0.09	.06	1.01		
Conscientiousness	-0.16	0.10	-.09	-1.71		
Neuroticism	0.15	0.08	.11	1.85		
Openness	-0.24	0.09	-.14	-2.65**		
Block 3: Motives for TikTok Use					.010	.006
Socially rewarding self-presentation	0.02	0.02	.06	1.00		
Trendiness	0.01	0.07	.01	0.12		
Escapist addiction	0.06	0.05	.07	1.15		
Novelty	-0.17	0.18	-.05	-0.91		

Notes: $N = 361$; *$p < .05$; **$p < .01$; ***$p < .001$; 0 = male, 1 = female. 0 = United States of America, 1 = United Kingdom. 0 = older user, 1 = younger user. *SE B* = Standard Error of Beta.

4.2.10. Hierarchical regression model of predictors with the total number of hours spent on TikTok as the outcome variable

For hours spent on TikTok during the past week (combining day-time and night-time), results showed that in the first block, demographic factors contributed significantly to the regression model, $F(3, 357) = 14.64$, $p < .001$, $R^2 = .081$, $R^2_{adjusted} = .074$, and accounted for 8.1% of the variance. Age (β = .12, $t = 2.40$, $p = .017$), gender (β = .12, $t = 2.35$, $p = .019$), and nationality (β = .21, $t = 4.20$, $p < .001$) all positively and significantly predicted TikTok use across the whole week, supporting H3 (Demographic factors (age, gender, and nationality) will significantly predict TikTok use). For complete analysis outputs, see Appendix Y.

For the second block analysis, personality traits also contributed significantly to the regression model, $\Delta F(5, 355) = 4.49$, $p < .001$, $R^2 = .115$, $R^2_{\text{adjusted}} = .095$, and accounted for 5.9% of the variance. Extraversion ($\beta = .11$, $t = 1.99$, $p = .047$) and neuroticism ($\beta = .14$, $t = 2.40$, $p = .017$) both positively and significantly predicted TikTok use across the whole week, supporting H4a (Higher scores in extraversion, openness, neuroticism will significantly predict higher TikTok use). However, openness ($\beta = -.16$, $t = -3.03$, $p = .003$) negatively and significantly predicted TikTok use across the whole week, partially supporting H4a overall. Conscientiousness ($\beta = -.11$, $t = -2.06$, $p = .040$) and agreeableness ($\beta = .09$, $t = 1.70$, $p = .091$) did not significantly predict TikTok use across the whole week, so H4b (Higher scores in agreeableness and conscientiousness will significantly predict lower TikTok use) was not supported. For complete analysis outputs, see Appendix Z.

In the final block analysis, motives for TikTok use did not significantly contribute to the regression model, $\Delta F(4, 356) = 1.77$, $p = .135$, $R^2 = .124$, $R^2_{\text{adjusted}} = .094$, and collectively accounted for 1.9% of the variance. Socially rewarding self-presentation ($\beta = .05$, $t = .79$, $p = .432$), trendiness ($\beta = .03$, $t = .43$, $p = .669$), and novelty ($\beta = -.06$, $t = -1.08$, $p = .279$) did not significantly predict TikTok usage across the whole week, so H5 (Higher scores of motives for TikTok use (socially rewarding self-presentation, trendiness, escapist addiction, novelty) will significantly predict higher levels of TikTok use) was not supported. Escapist addiction ($\beta = .12$, $t = 1.98$, $p = .049$) positively and significantly predicted TikTok usage across the whole week, supporting H5. For complete analysis outputs, see Appendix AA.

In summary, being young, female, British, more extraverted, more neurotic, less conscientious, less open to experience, and more motivated to escape were related to higher levels of TikTok usage. Regression coefficients are presented in Table 9.

Table 9.

Hierarchical regression model for the total number of hours spent on TikTok in the past week (combination of day-time and night-time).

Predictor	*B*	*SE B*	β	*t*	R^2	ΔR^2
Block 1: Demographic Factors					.081	.074***
Age	1.89	0.79	.12	2.40*		
Gender	1.87	0.80	.12	2.35*		
Nationality	3.25	0.78	.21	4.20***		
Block 2: Personality Traits					.06	.09***
Extraversion	0.38	0.19	.11	1.99*		
Agreeableness	0.34	0.20	.09	1.70		
Conscientiousness	-0.45	0.22	-.11	-2.06*		
Neuroticism	0.45	0.19	.14	2.40*		
Openness	-0.62	0.20	-.16	-3.03**		
Block 3: Motives for TikTok Use					.02	.13
Socially rewarding self-presentation	0.04	0.05	.05	0.79		
Trendiness	0.07	0.17	.03	0.43		
Escapist addiction	0.24	0.12	.12	1.98*		
Novelty	-0.45	0.42	-.06	-1.08		

Notes: N = 361; **p* < .05; ***p* < .01; ****p* < .001; 0 = male, 1 = female. 0 = United States of America, 1 = United Kingdom. 0 = older user, 1 = younger user. *SE B* = Standard Error of Beta.

4.2.11. Hierarchical regression model of predictors with the number of times TikTok was opened during the day as the outcome variable

For the number of times TikTok was opened during the day-time, results showed that in the first block, demographic factors contributed significantly to the regression model, $F(3, 357) = 7.382$, $p < .001$, $R^2 = .058$, $R^2_{adjusted} = .050$, and accounted for 5.8% of the variance. Age (β = .22, t = 4.31, $p < .001$) positively and significantly predicted the number of times users opened TikTok, supporting H3 (Demographic factors (age, gender, and nationality) will significantly predict TikTok use). Gender (β = .05, t = .97, p = .331) and nationality (β = .06, t = 1.20, p = .230) did not significantly predict the number of times users opened TikTok, so H3 was not supported. For complete analysis outputs, see Appendix AB.

For the second block analysis, personality traits did not significantly contribute to the regression model, $\Delta F(5, 355) = 1.67$, $p = .142$, $R^2 = .078$, $R^2_{\text{adjusted}} = .057$, and accounted for 2.3% of the variance. Extraversion (β = .05, $t = .78$, $p = .434$) and neuroticism (β = .04, $t = .63$, $p = .527$) did not significantly predict the number of times users opened TikTok during the day, so H4a (Higher scores in extraversion, openness, neuroticism will significantly predict higher TikTok use) was not supported. Openness (β = -.12, $t = -2.27$, $p = .024$) negatively and significantly predicted the number of times users opened TikTok during the day, also not supporting H4a. Agreeableness (β = .01, $t = .23$, $p = .822$) and conscientiousness (β = -.08, $t = -1.54$, $p = .125$) did not significantly predict the number of times users opened TikTok during the day, so H4b (Higher scores in agreeableness and conscientiousness will significantly predict lower TikTok use) was not supported. For complete analysis outputs, see Appendix AC.

In the final block analysis, motives for TikTok use did significantly contribute to the regression model, $\Delta F(4, 356) = 9.07$, $p < .001$, $R^2 = .092$, $R^2_{\text{adjusted}} = .082$, and accounted for 9.2% of the variance. Socially rewarding self-presentation (β = -.03, $t = -.56$, $p = .579$), trendiness (β = .004, $t = .06$, $p = .949$), and novelty (β = -.03, $t = -.60$, $p = .547$) did not significantly predict the number of times users opened TikTok during the day, so H5 (Higher scores of motives for TikTok use (socially rewarding self-presentation, trendiness, escapist addiction, novelty) will significantly predict higher levels of TikTok use) was not supported. Escapist addiction (β = .31, $t = 5.49$, $p < .001$) positively and significantly predicted the number of times users opened TikTok during the day, supporting H5. For complete analysis outputs, see Appendix AD.

In summary, being young, less open to experience, and motivated to escape were related to opening TikTok more frequently during the day. Regression coefficients are shown in Table 10.

Table 10.

Hierarchical regression model for the number of times TikTok was opened in the past week during day-time (6am-10pm).

Predictor	*B*	*SE B*	β	*t*	R^2	ΔR^2
Block 1: Demographic Factors					.058	.050***
Age	36.58	8.48	.22	4.31***		
Gender	8.34	8.57	.05	0.97		
Nationality	10.05	8.35	.06	1.20		
Block 2: Personality Traits					.02	.14
Extraversion	1.63	2.08	.05	0.43		
Agreeableness	0.50	2.20	.01	0.82		
Conscientiousness	-3.63	2.36	-.08	0.13		
Neuroticism	1.28	2.01	.04	0.53		
Openness	-5.03	2.21	-.12	0.02*		
Block 3: Motives for TikTok Use					.09	.07***
Socially rewarding self-presentation	-0.28	0.51	-.03	-0.56		
Trendiness	0.11	1.72	.004	0.95		
Escapist addiction	6.68	1.22	.31	< .001***		
Novelty	-2.57	4.26	-.03	0.55		

Notes: N = 361; **p* < .05; ***p* < .01; ****p* < .001; 0 = male, 1 = female. 0 = United States of America, 1 = United Kingdom. 0 = older user, 1 = younger user. *SE B* = Standard Error of Beta.

4.2.12. Hierarchical regression model of predictors with the number of times TikTok was opened at night as the outcome variable

For the number of times TikTok was opened during night-time, results showed that in the first block, demographic factors contributed significantly to the regression model, $F(3, 357) = 5.85$, $p < .001$, $R^2 = .047$, $R^2_{adjusted} = .039$, and accounted for 4.7% of the variance. Age (β = .20, $t = 3.80$, $p < .001$) positively and significantly predicted how many times users open TikTok at night, supporting H3 (Demographic factors (age, gender, and nationality) will significantly predict TikTok use). Gender (β = .02, $t = .36$, $p = .717$) and nationality (β = .07, $t = 1.36$, $p = .173$) did not significantly predict how many times users opened TikTok, which did not support H3, thus partially supporting H3 overall. For complete analysis outputs, see Appendix AE.

For the second block analysis, personality traits did not significantly contribute to the regression model, $\Delta F(5, 355) = 1.55$, $p = .172$, $R^2 = .068$, $R^2_{adjusted} = .046$, and accounted for 2.1% of the variance. Extraversion ($\beta = -.02$, $t = -.32$, $p = .751$), neuroticism ($\beta = .01$, t = .17, p = .866), and openness did not significantly predict how many times users opened TikTok at night, so H4a (Higher scores in extraversion, openness, neuroticism will significantly predict higher TikTok use) was not supported. Conscientiousness ($\beta = -.10$, $t = -1.83$, $p = .068$) and agreeableness ($\beta = .08$, $t = 1.43$, $p = .152$) did not significantly predict how many times users opened TikTok at night, so H4b (Higher scores in agreeableness and conscientiousness will significantly predict lower TikTok use) was also not supported. For complete analysis outputs, see Appendix AF.

In the final block analysis, motives for TikTok use significantly contributed to the regression model, $\Delta F(4, 356) = 3.13$, $p < .015$, $R^2 = .034$, $R^2_{adjusted} = .023$, and collectively accounted for 3.4% of the variance. Socially rewarding self-presentation ($\beta = .05$, $t = .89$, $p = .375$), trendiness ($\beta = .01$, $t = .20$, $p = .842$), and novelty ($\beta = -.04$, $t = -.64$, $p = .526$) did not significantly predict how many times users opened TikTok at night, so H5 (Higher scores of motives for TikTok use (socially rewarding self-presentation, trendiness, escapist addiction, novelty) will significantly predict higher levels of TikTok use) was not supported. Escapist addiction ($\beta = .17$, $t = 2.92$, $p = .004$) positively and significantly predicted how many times users opened TikTok, partially supporting H5 overall. For complete analysis outputs, see Appendix AG.

In summary, being young and motivated to escape were associated with opening TikTok more frequently at night. Regression coefficients are presented in Table 11.

Table 11.

Hierarchical regression model for the number of times TikTok was opened in the past week during night-time (10pm-6am).

Predictor	*B*	*SE B*	β	*t*	R^2	ΔR^2
Block 1: Demographic Factors					.047	.039***
Age	15.76	4.15	.20	3.80***		
Gender	1.52	4.19	.02	0.36		
Nationality	5.58	4.09	.07	1.36		
Block 2: Personality Traits					.02	.11
Extraversion	-0.32	1.01	-.02	-0.32		
Agreeableness	1.54	1.07	.08	1.44		
Conscientiousness	-2.10	1.15	-.10	-1.83		
Neuroticism	0.17	0.98	.01	0.17		
Openness	-1.65	1.08	-.08	-1.53		
Block 3: Motives for TikTok Use					.03	.10*
Socially rewarding self-presentation	0.23	0.26	.05	0.89		
Trendiness	0.17	0.86	.01	0.20		
Escapist addiction	1.79	0.61	.17	2.92**		
Novelty	-1.36	2.14	-.04	-0.64		

Notes: N = 361; *$p < .05$; **$p < .01$; ***$p < .001$; 0 = male, 1 = female. 0 = United States of America, 1 = United Kingdom. 0 = older user, 1 = younger user. *SE B* = Standard Error of Beta.

4.2.13. Hierarchical regression model of predictors with the total number of times TikTok was opened as the outcome variable

For number of times TikTok was opened in the past week (combining day-time and night-time), results showed that in the first block, demographic factors contributed significantly to the regression model, $F(3, 357) = 8.29$, $p < .001$, $R^2 = .065$, $R^2_{adjusted} = .057$, and accounted for 6.5% of the variance. Age (β = .24, t = 4.56, $p < .001$) positively and significantly predicted how many times users opened TikTok, supporting H3 (Demographic factors (age, gender, and nationality) will significantly predict TikTok use). Gender (β = .04, t = 0.85, p = .395) and nationality (β = .07, t = .1.38, p = .167) did not significantly predict how many times users opened

TikTok, which did not support H3, thus partially supporting H3 overall. For complete analysis outputs, see Appendix AH.

For the second block analysis, personality traits did not contribute significantly to the regression model, $\Delta F(5, 355) = 1.81$, $p = .111$, $R^2 = .025$, $R^2_{\text{adjusted}} = .011$, and accounted for 2.5% of the variance. Extraversion ($\beta = .03$, $t = .46$, $p = .643$) and neuroticism ($\beta = .03$, $t = .53$, $p = .598$) did not significantly predict how many times users opened TikTok across the whole week, while openness ($\beta = -.12$, $t = -2.23$, $p = .027$) negatively and significantly predicted how many times users opened TikTok across the whole week, so H4a (Higher scores in extraversion, openness, neuroticism will significantly predict higher TikTok use) was not supported. Agreeableness ($\beta = .04$, $t = .68$, $p = .496$) and conscientiousness ($\beta = -.10$, $t = -1.79$, $p = .074$) did not significantly, predict how many times users opened TikTok across the whole week, so H4b (Higher scores in agreeableness and conscientiousness will significantly predict lower TikTok use) was not supported. For complete analysis outputs, see Appendix AI.

In the final block analysis, motives for TikTok use significantly contributed to the regression model, $\Delta F(4, 356) = 7.93$, $p < .001$, $R^2 = .082$, $R^2_{\text{adjusted}} = .072$, and collectively accounted for 8.2% of the variance. Socially rewarding self-presentation ($\beta = -.01$, $t = -.10$, $p = .936$), trendiness ($\beta = .01$, $t = .12$, $p = .905$), and novelty ($\beta = -.04$, $t = -.68$, $p = .500$) did not significantly predict how many times users opened TikTok across the whole week, so H5 (Higher scores of motives for TikTok use (socially rewarding self-presentation, trendiness, escapist addiction, novelty) will significantly predict higher levels of TikTok use) was not supported. Escapist addiction ($\beta = .29$, $t = 5.10$, $p < .001$) positively and significantly predicted how many times users opened TikTok across the whole week, partially supporting H5 overall. For complete analysis outputs, see Appendix AJ.

In summary, being young, less open to experience, and motivated to escape were related to opening TikTok more frequently. Regression coefficients are presented in Table 12.

Table 12.

Hierarchical regression model for the total number of times TikTok was opened in the past week (combination of day-time and night-time).

Predictor	*B*	*SE B*	β	*t*	R^2	ΔR^2
Block 1: Demographic Factors					.10	.10***
Age	-2.84	0.48	-.30	-5.91***		
Gender	8.57	11.38	.04	0.75		
Nationality	10.63	11.16	.05	0.95		
Block 2: Personality Traits					.03	.15
Extraversion	1.31	2.82	.03	0.46		
Agreeableness	2.03	2.98	.04	0.68		
Conscientiousness	-5.73	3.20	-.10	-1.79		
Neuroticism	1.44	2.73	.03	0.53		
Openness	-6.69	3.00	-.12	-2.23*		
Block 3: Motives for TikTok Use					.08	.09***
Socially rewarding self-presentation	-0.06	0.70	-.01	-0.08		
Trendiness	0.28	2.35	.01	0.12		
Escapist addiction	8.47	1.66	.29	5.10***		
Novelty	-3.92	5.81	-.04	-0.68		

Notes: $N = 361$; *$p < .05$; **$p < .01$; ***$p < .001$; 0 = male, 1 = female. 0 = United States of America, 1 = United Kingdom. 0 = older user, 1 = younger user. *SE B* = Standard Error of Beta.

4.2.14. Hierarchical regression summary

In summation, overall explanation of the variance of TikTok usage in hours by demographic factors was 8.1%, by personality traits was 5.9%, and by motives for use was 1.9%. Explanation of the total variance in usage by the number of times TikTok was opened by demographic factors was 6.5%, by personality traits was 2.5%, and by motives for use was 8.2%. Those with more frequent TikTok usage in hours were more likely to be young, female, British, non-conscientious, more extraverted and neurotic, less open to experience, and were more motivated to escape. TikTok users who opened the app more frequently were more likely to be young, less open to experience, and more motivated to escape.

5. Discussion

The current study extended upon existing literature by investigating the role of demographic factors, personality traits and user motivations in predicting TikTok use based on objectively recorded data. This study is also the first to employ the Motives for TikTok Use measure designed by Scherr and Wang (2021) with a sample from various age groups in the United Kingdom and the United States of America, two examples of Western countries in which TikTok's popularity has increased since the COVID-19 pandemic (Ceci, 2023a; Gottfried, 2024). The present study's findings will be discussed by focusing on each of the three types of predictors: demographic factors (H1a-c), personality traits (H2), and motives for use (H3), as well as how each predictor may influence TikTok use across the UK and USA (RQ). This study comprised individuals aged 18 – 68 years with a range of student and other employment statuses, which was unlike other studies into SMU, which typically employ solely student or adolescent samples (Alhabash & Ma, 2017; Cleofas et al., 2022; Günlü et al., 2023; Kircaburun et al., 2020; Qin et al., 2023; Sha & Dong, 2021; Tian et al., 2022). Also, there were more female than male respondents in this sample, which was opposite to some studies (Kay et al., 2017) but predominantly similar to others (Boyle et al., 2022; Kircaburun et al., 2020; Stefanone et al., 2011; Vaterlaus & Winter, 2021). This may be explained by the impact of gender on online research participation, women more likely to participate in online surveys than men (Smith, 2008).

5.1. Summary of key findings

5.1.1 There will be a significant difference between the number of hours users self-report spending on TikTok compared to in-app data (H1)

Results from a paired samples student's t-test revealed a significant difference between the number of hours users think they spent on TikTok compared to actual in-app recorded data, supporting this hypothesis. Specifically, users tended to overestimate the amount of time they spent on the platform; while self-reported usage was an average of 9 hours and 58 minutes per week, in-app recorded data indicated an average of 4 hours and 58 minutes per week, showing a clear and statistically significant difference. This finding suggests that users may have difficulty recalling or have limited awareness of their SMU, supporting the notion that relying on subjective self-reports may not be the most appropriate method in recording SMU (Mahalingham et al., 2023; Parry et al., 2021; Yao et al., 2023). One possible explanation behind this discrepancy in hours spent on TikTok could be related to the app's design (Marek, 2023). TikTok encourages continuous engagement by scrolling through content tailored to the users via the algorithm (PItre, 2023), which may result in the user losing track of time or experiencing loss of time perception while using the app (Ernala et al., 2020; Sewall et al., 2020).

5.1.2 There will be a significant difference between the number of times users self-report opening TikTok compared to in-app data (H2)

Results from a paired samples student's t-test revealed a significant difference between the number of times users self-reported they opened TikTok compared to actual in-app recorded data, supporting this hypothesis. In contrast to the number of hours spent on TikTok, users tended to underestimate how many times they opened the app. While the self-reported number of times opened averaged at 44 times per week, in-app data revealed an average of 89 times per week, also showing a clear and statistically significant difference. These findings suggest that users, similar to the time spent on TikTok, may have limited awareness of how often they access the app. Users may also not perceive quick or habitual openings as distinct 'uses' and may not report them. This supports existing research which argues that users find it difficult to estimate and self-report habitual digital behaviours (Meier, 2021; Yang et al., 2024). The automative nature of app-checking already discussed in past research (Burnell et al., 2021), may also contribute to this underestimation. Using TikTok may involve opening the app frequently or unintentionally for very short periods of time, such as out of habit, and thus users may experience gaps in their memory while trying to recall every instance they accessed TikTok across an entire week. Together with the overestimation of time spent on the app, these findings contribute to a broader trend of misperceptions in self-reported SMU, highlighting the importance of incorporating objective measures in future media use research.

5.1.3 Younger users will show significantly higher levels of actual TikTok use than older users (H3a)

Results from an independent samples t-test revealed a significant difference between younger and older users and their TikTok usage. Specifically, younger users were found to spend significantly more time on TikTok and open TikTok significantly more frequently than older users, supporting this hypothesis. According to in-app data, younger users spent an average of 5 hours and 33 minutes on TikTok per week, while older users spent an average of 3 hours and 23 minutes on TikTok per week. Younger users opened TikTok an average of 104 times per week according to in-app data, slightly more than double the number of times for older users, which was an average of 50 times. The finding that younger individuals are more likely to use TikTok for longer and open the app more frequently aligns with previous research supporting the argument that SMP are typically used by younger age groups or younger generations (Auxier & Anderson, 2021; Ceci, 2023b; Huang & Su, 2018; Vogels et al., 2022).

However, this does not suggest that older individuals do not use social media; they may simply use it less frequently or for different reasons (Ng & Indran, 2022, 2023; Zhao et al., 2023). Another possible explanation for those who may be older than Gen Z users, for instance, but still have a higher frequency of SMU, may require using SMP such as TikTok for work purposes, particularly if content creation is their only profession or source of income (Johnson et al., 2022; Tanachot, 2021). It is also possible that usage may have increased for those who are employed or working in hybrid or flexitime conditions since they were introduced during the COVID-19 pandemic (Singh et al., 2021). So, it is unclear how many working participants are still working from home. However, within the hierarchical regression, age was dummy coded with 1 coded as users aged 34 years or younger and 0 as users 35 years or older. It may be difficult to interpret whether a specific age or more narrowed age range would better contribute to the model.

5.1.4 Female users will show significantly higher levels of actual TikTok use than male users (H3b)

Results from an independent samples t-test revealed a significant difference between female and male users and the number of hours they spent on TikTok. According to in-app data, female users spent an average of 5 hours and 28 minutes on TikTok per week, while male users spent an average of 3 hours and 30 minutes per week, showing a statistically significant difference, supporting this hypothesis. In regard to the number of times users opened TikTok, female users opened TikTok an average of 92 times according to in-app data, while male users opened the app an average of 82 times. While female users opened TikTok more frequently than male users, this difference was not statistically significant, not supporting this hypothesis. The finding that females use TikTok more than males supports past research into other SMP, such as Instagram and Facebook, which revealed similar findings (McAndrew & Jeong, 2012; Scott et al., 2017; Sheldon & Bryant, 2016). However, this may only be consistent across specific SMP, some of which are argued to be used by men more than women, such as YouTube or Twitter (Kircaburun et al., 2020; Laor, 2022).

It is also necessary to consider that men and women may have different motivations for SMU, which influences the amount of time or how often they check social media. For instance, women tend to prefer content focused on relatability or a popular trend, while men tend to use social media for meeting new people or entertainment (Alruwaili, 2017; Cleofas et al., 2022; Kircaburun et al., 2020; Vaterlaus & Winter, 2021; West et al., 2015). While the differences outlined in this study could potentially be influenced by different motivations amongst men and women, this study did not explore motivational factors across genders in depth. While demographic data, including gender, were collected, examining the underlying motivations for TikTok use across genders was beyond the scope of the current study. A post-hoc analysis was not conducted because the current study did not have a theoretical framework or prior hypothesis to guide conducting this analysis, and any conclusions drawn without these elements would be speculative and uncertain. Future research could build on these findings by investigating gender-specific motivations in regard to self-perceptions of screen time and user motivation.

5.1.5 There will be significant difference in actual TikTok use between UK and USA users (H3c)

Results from an independent samples t-test revealed a significant difference between UK and USA users and the number of hours they spent on TikTok. According to in-app data, UK users spent more time on TikTok, an average of 5 hours and 57 minutes per week, than USA users, who spent an average of 2 hours and 27 minutes on TikTok per week. This showed a clear and statistically significant difference, supporting this hypothesis. However, while UK users opened TikTok more frequently per week than USA users, an average of 95 times compared to 74 times, respectively. This difference was not statistically significant, thus not supporting H5. The finding that individuals from the UK spend longer on TikTok and open TikTok more frequently may be potentially influenced by the proportion of UK users within the study's sample (72.3% vs 27.7% being USA users). This uneven distribution may have influenced the results, as the larger number of UK participants means their usage patterns had more impact on the overall findings. Because of this, it's harder to tell whether the differences between UK and US users are actually due to nationality or just a result of the sample composition. This imbalance between the two groups makes it difficult to generalise the findings, so future research would benefit from having a more even mix of participants from each country to allow for clearer and more generalisable comparisons.

Another reason usage may be higher for UK users is that the type of content users engage with may vary depending on where they are from. For instance, USA participants were not asked which state they were from, which may have revealed further insight into their social media platform and content preferences, which may differ across states. This also makes generalising the USA proportion of the sample more difficult; the present study's 100 participants could assume an average of 2 people from each state, making generalisability even less possible. This may also be the case with individuals from the UK, as participants were not asked if they were from England, Scotland, Wales, or Northern Ireland, which may also impact on their SMU or content preferences. As both countries are predominantly individualistic, it is logical to assume that certain types of content, trends, or challenges may be consistent across both countries and state or regions within those countries. For instance, Pick et al. (2019) found that Twitter users were in southern California and in the Mississippi region, while Facebook users were more prevalent in Colorado, Utah, and the adjacent Rocky Mountain States (Montana, Idaho, Washington, Wyoming, and New Mexico). For a UK example, Ofcom (2024) reported internet users in Northern Ireland are likely to engage with more platforms than England, Wales, and Scotland (p.9). Without this level of detail, it may be difficult to generalise the findings from both countries, as regional variation may be an influential factor in cross-cultural SMU research.

Age differences in the UK and the USA may also impact on user motivation. For instance, the age for educational milestones such as going to university is different to those in the USA, which may be reflected in their social media habits. Age in both countries also affects other milestones, such as when individuals can drink, drive, or start working may also play a role in differences in TikTok use. So, future research should be recommended to investigate further into specific regions in both countries, where usage may be influenced by lifestyle, professional, societal norms, or political differences specific to regions or states in the UK and USA, respectively. Some cultural differences between the UK and USA could also be explained by higher scores of extraversion and agreeableness. As users from individualistic cultures may demonstrate higher scores in these traits similar to the present study, this could also be related to increased social interactions implemented through TikTok.

5.1.6 Demographic factors (age, gender, and nationality) will significantly predict TikTok use (H3)

Hierarchical regression results for H1 indicated that age, gender, and nationality were all significant predictors of TikTok usage in hours during the day, supporting the hypothesis. However, only age was a significant predictor of TikTok use in hours during the night or across the week as a whole, while gender and nationality were not, which does not support H6. Across the demographic factors, only some predictors significantly explained TikTok use. Younger and UK users showed higher levels of use across several outcomes, while gender effects were mixed and often non-significant.

5.1.7 Age as a predictor of TikTok use

Hierarchical regression results revealed that age was a significant predictor of TikTok use across all outcome variables, supporting this hypothesis. Age also showed a positive association with higher levels of TikTok use, indicating that younger users (18 to 34 years) were more likely to use TikTok for longer and open the app more frequently than older users (35+ years). These findings appear consistent with prior research that indicates younger adults are generally more active on SMP (Alhabash & Ma, 2017; Deng et al., 2023). TikTok, in particular, has become embedded in the culture of younger people due to its emphasis on UGC, short-form videos, trends, and personalised 'For You' pages with algorithmically curated content (Anderson, 2020; Putro & Palupi, 2022; Santos, 2021). Younger social media users are also referred to as social media natives, who have grown up or are more accustomed to social media being more present in day-to-day life (Borges, 2023; Bowe & Wohn, 2015). As such, they are also likely to be familiar with the rapid consumption of entertaining, creative, and unique content on TikTok.

Additionally, U&G theory may further explain this age-related difference in TikTok usage. Younger users may be more likely to turn to TikTok for various reasons, such as escapism, social interaction, or self-expression, all of which are important needs during early adulthood (Cleofas et al., 2022; Shao & Lee, 2020; Vaterlaus & Winter, 2021). On the other hand, older users may be less motivated by these factors or rely on other platforms that better fit their needs and online habits (Blank & Lutz, 2017). It is also possible attitudes toward data protection and privacy, digital literacy, and perceived importance of time spent on social media contribute to this difference in usage between age groups. For example, older users may be more cautious or selective in their app usage, which could explain less time spent on TikTok and reduced frequency in opening the app itself.

5.1.8 Gender as a predictor of TikTok use

Hierarchical regression results revealed that gender was a significant predictor of TikTok use in hours during the day and across the whole week. However, gender was not a significant predictor for hours spent on TikTok at night, or any outcome variables for the number of times users opened TikTok, partially supporting this hypothesis. Although some coefficients were positive, gender was not a significant predictor for several outcome variables, so no conclusions can be drawn about differences in how often male and female users open TikTok. While gender was not a statistically significant predictor of TikTok use, the pattern surrounding female users on social media supports previous research. Women have been found to be more active on SMP that emphasise visual content and encourage establishing social connections (Alruwaili, 2017; Cleofas et al., 2022; Laor, 2022), and TikTok appears to follow this pattern.

In particular, TikTok emphasizes community engagement, trends and self-expression, all of which may appeal more to female users, which could explain their higher levels of usage. In regard to the non-significant results, they could also be due to sample size limitations or variability between gender groups. Future research should take into account the possibility that while gender alone is not a strong predictor, it may interact with other factors, such as age, personality, content preferences, or other motivations not explored in the current study, which could influence usage more considerably. Therefore, this highlights the complexity of online behaviour, where demographic, psychological, and other variables often influence or intersect with one another.

5.1.9 Nationality as a predictor of TikTok use

Hierarchical regression results revealed that nationality was a significant predictor of TikTok use in hours, but not a significant predictor of how often users opened TikTok. Therefore, no conclusions can be drawn about differences between how frequently UK and USA users opened the app. Similarly, nationality also showed a positive association for the number of hours users spent on TikTok, with UK users more likely to spend longer on TikTok than USA users, but this difference was statistically significant. Like gender, nationality did not significantly predict TikTok usage overall, which may reflect cultural or contextual differences surrounding how TikTok is used as an SMP in each country. For example, users from the UK may engage with or participate in content that is localised to them, whereas USA users may not show interest in or be shown this content. Also, TikTok's popularity and cultural impact may differ between the two countries at specific periods, such as current events and media coverage, the presence of influencers, or what is trending at the time. Further differences between the UK and USA impacting the present study are discussed in Section 5.5.

5.1.10 Extraversion, openness, neuroticism, agreeableness and conscientiousness will significantly predict TikTok use (H4)

Hierarchical regression results indicated that extraversion, conscientiousness, neuroticism, and openness were significant predictors of TikTok usage for at least two outcome variables, while agreeableness was not, not supporting this hypothesis overall. Conscientiousness was a significant predictor for hours spent on TikTok during the day-time and during the week overall, with lower conscientiousness associated with greater use. Extraversion, neuroticism, and openness were also significant predictors of the number of hours spent on TikTok. Openness was the only significant predictor for the number of times users opened TikTok, and those scoring low in openness were more likely to use TikTok for longer both during the day and at night. Furthermore, individuals scoring higher on extraversion were more likely to use TikTok for longer at night-time, while those lower in conscientiousness and higher in neuroticism were more likely to use TikTok for longer during the day.

5.1.11 Higher scores in extraversion, openness, neuroticism will significantly predict higher TikTok use (H4a)

Extraversion. Hierarchical regression results found extraversion to be a significant predictor of the number of hours spent on TikTok during night-time (10pm - 6am) and during the week overall. Also, extraversion was found to be a non-significant predictor of the number of times users open TikTok, thus partially supporting this hypothesis, but no conclusions can be drawn about its relationship with TikTok usage behaviour. The role of extraversion in higher durations of SMU supports the notion that extroverted individuals are more likely to spend more time on social media, as found in past research (Bowden-Green et al., 2020; Ryan & Xenos, 2011). In the case of TikTok and opportunities for social interaction or frequent posting, the present study could be expanded upon to clarify that these specific behaviours result in increased usage in extroverted individuals. Furthermore, due to the nature of TikTok and opportunities for community building and support since the COVID-19 pandemic, increased duration of usage may imply that extraverted individuals use TikTok as a tool for self-expression without fear of other's opinions (D'Agata & Kwantes, 2020). This could also be the case with more introverted individuals, as social media has been found to make online interactions easier for those who struggle with offline interactions (Philip & Zakkariya, 2016). The significance of extraversion as a predictor only during night-time was particularly interesting. As most of the study's sample comprised users who were in education or some form of employment, it seems likely that TikTok usage would increase outside of typical working hours (such as 9am - 5pm, Monday to Friday). Also, it is unclear if other confounds could affect usage in these individuals, such as students who also work, users who have dependents, such as children, or users whose work hours may be more irregular.

While extraversion was not a significant predictor for how often users open TikTok, there are some potential explanations for this. One possible explanation is more extroverted users may spend longer on TikTok in a single use, but open the app less frequently as a result. As suggested in past research, extroverted individuals are more likely to post more frequently and participate in trends or challenges (Da-yong & Zhan, 2022; Krisadhi et al., 2023). Therefore, those who post more frequently may be provoked by features on TikTok to engage with the app for longer periods of time to create and edit content, for instance. In previous research, extroverted individuals have been found to have more friends or followers on social media (Amichai-Hamburger & Vinitzky, 2010), and this could also be the case with TikTok. If an individual is more extroverted, they may wish to directly engage with other users, thus spending more time on the app.

Future research into this form of usage could investigate motivations for opening SMP, such as responding to notifications. Also, examining age and personality could be a promising point of interest for future research. Higher levels of TikTok use coupled with high extraversion scores in a younger demographic may be linked to developmental psychological theories, such as Erikson's (1950; 1959) theory of psychosocial development. His theory suggests that adolescents and young adults are typically focused on building their self-identity and social relationships, in the context of social media, TikTok may serve as a suitable online platform for fulfilling those social needs.

Openness. Openness was found to be a significant predictor across all but one outcome variable: the number of times users opened TikTok at night-time. Openness also showed a negative association with TikTok usage, indicating that those who scored lower in openness spent more time on TikTok or opened the app more frequently, thus not supporting this hypothesis. While openness was found to be a statistically significant predictor of TikTok usage across five outcome variables, it is important to note that the block of personality traits as a whole accounted for a small percentage of variance in usage outcomes for how often users opened TikTok during the day ($\Delta R^2 = 0.23$), at night ($\Delta R^2 = 0.21$), and in total ($\Delta R^2 = 0.25$). This suggests that, although statistically significant, the predictive power of openness, and the personality traits block as a whole, is likely to be limited in its practical impact in predicting TikTok usage. These findings appear inconsistent with previous research, which argues that openness is positively associated with increased SMU (Correa et al., 2010; Zhang et al., 2011). The present study's findings were also inconsistent with past research that found no relationship between openness and SMU, with openness more associated with searching behaviour (Moore & McElroy, 2012). However, this study explored Facebook, and therefore, is difficult to compare to TikTok due to both the platforms' designs and user interfaces.

Individuals high in openness tend to be curious, imaginative and broad-minded (Barrick & Mount, 1991). So, the notion that lower levels of openness are associated with TikTok usage could be related to TikTok's algorithmically curated content. As such, it could be assumed that users low in openness spend more time on TikTok and see content suited to their preferences already shown on their 'For You' page. As the content is already provided, users may not be willing to openly seek new content or may engage in PSMU by watching content, as opposed to users who create content. Furthermore, as openness was a significant predictor of the number of times users open TikTok, this also brings an interesting point of discussion forward. Users who score low in openness may open TikTok more frequently also due to familiarity with the online environment. For example, they may have specific accounts that they follow or types of content that they like, and so the algorithm will ensure they continue to see content of this type or from a specific account, creating a narrower range of interests and preventing them from exploring new or imaginative content.

Neuroticism. Neuroticism was found to be a significant predictor of the number of hours spent on TikTok, particularly during the day-time (10am - 6pm) and during the week overall. However, neuroticism was not found to be a statistically significant predictor of the number of times users opened TikTok, thus partially supporting this hypothesis. Individuals high in neuroticism tend to be more prone to emotional instability or feelings of anxiety and seek comfort or assurance through online interactions as opposed to offline interactions (Correa et al., 2010; Hughes et al., 2012; Widiger, 2009). The notion that neurotic individuals would spend more time on TikTok supports this idea of finding comfort, as TikTok has been shown to be a useful tool for seeking out other users with common interests or providing safe spaces for self-expression (Flood, 2021; Griffiths, 2023; Şot, 2022). In contrast, these findings are inconsistent with research by Ponce (2023), who argues that more neurotic individuals would prefer to post on more text-based platforms, such as Twitter, as opposed to using videos on TikTok. Also, most research which looks into neuroticism and its role in SMU, addictive or problematic social use is predominantly explored (Blackwell et al., 2017; Marino et al., 2016; Ponce, 2023). The present study explored an average week in usage without consideration for problematic or addictive usage. So, this makes comparing the present study to past research more difficult due to the outcome variables being different. However, increased time spent on TikTok could also consist of passively watching other users' content without creating content. So, future research should look into content preferences on TikTok, whether users prefer to watch or create content, and their relationship with personality.

On the other hand, neuroticism was found to be a non-significant predictor of the number of times users opened TikTok, and so no conclusions can be drawn on the influence of neuroticism on this usage behaviour. This appears inconsistent with past research as neurotic individuals are expected to spend more time on social media (Correa et al., 2010; Hughes et al., 2012). Another reason for opening TikTok less frequently could be due to social media fatigue, in which feelings of overwhelm or increased time on social media may lead to the user avoiding social media (Appel et al., 2019; Wang & Scherr, 2021). This highlights how often users open TikTok could lead to further investigation surrounding chances for digital or social media fatigue, and how personality traits could play a role in exploring how users are more or less susceptible to social media fatigue.

5.1.14 Higher scores in agreeableness and conscientiousness will significantly predict lower TikTok use (H4b)

Agreeableness. Agreeableness was found to be a non-significant predictor of the number of hours users spent on TikTok and how many times users opened TikTok, therefore not supporting this hypothesis. As such, no conclusions can be drawn on the effect of agreeableness on TikTok usage behaviour. The non-significant effect of agreeableness on TikTok usage appears consistent with previous research where agreeableness is found to be significantly and positively associated with how SMU benefits agreeable users (Seidman, 2013). However, little literature exists regarding relationships between agreeableness and the duration of SMU, so findings from the present study cannot be compared. Agreeableness refers to individuals who act helpful, friendly and sociable (Graziano & Eisenberg, 1997). They also typically have more friends on social media, such as Facebook, and also tend to post more content about themselves or respond positively to others (Moore & McElroy, 2012; Wang et al., 2012). However, little research appears to directly investigate agreeableness as a predictor of usage but rather as a variable which correlates with self-esteem or emotional stability, which, in turn, influences behaviour when on social media (Choi et al., 2017; Ross et al., 2009).

As previously stated in Chapter 2, individuals who score high in agreeableness may show friendly and helpful behaviours towards others. It appears the present study, which focused on duration or quantity of usage, was unable to uncover specific TikTok usage behaviour and its influence, if at all, on how users demonstrate agreeableness-related behaviour. Examples of this could be creating content to offer advice, telling a relatable story, or leaving positive comments to other users. In sum, exploring the amount of time spent on TikTok or the number of times users open the app may not have been an appropriate method for understanding agreeable TikTok users. So, future research should emphasise specific forms of content agreeable individuals engage with or how they conduct themselves when using TikTok.

Conscientiousness. Conscientiousness was found to be a significant predictor of the number of hours spent on TikTok, specifically during the day-time (6am – 10pm), and showed a negative association with TikTok usage across all outcome variables. On the other hand, conscientiousness did not significantly predict the number of times TikTok was opened, not supporting this hypothesis. Therefore, no conclusions could be drawn on the influence of conscientiousness on TikTok usage behaviour. Conscientious individuals tend to have a higher level of self-control (Anastasi & Urbina, 1997). So, it is expected from these findings that lower scores in conscientiousness was a significant predictor of more time spent on TikTok during certain times of the day. This could particularly be the case for younger users who may use TikTok as a means to escape day to day life, responsibilities or commitments, or to pass time (Brailovskaia et al., 2020; Nong et al., 2023; Uğur & Başak, 2018). This appears consistent with past research, which argued that conscientious individuals are less likely to spend more time on social media than those low in conscientiousness (Krisadhi et al., 2023; Marengo et al., 2020). These findings also support the argument in past research that increased SMU stems from boredom or procrastination (Da-yong & Zhan, 2022), but as this effect was non-significant, no conclusions can be drawn about conscientiousness and the frequency of users opening TikTok.

5.1.16 Higher scores of motives for TikTok use (socially rewarding self-presentation, trendiness, escapist addiction, novelty) will significantly predict higher levels of TikTok use (H5)

Hierarchical regression results indicated that escapist addiction significantly predicted TikTok usage across all but one outcome variables, while socially rewarding self-presentation, trendiness, and novelty did not, therefore partially supporting this hypothesis. Those who scored higher in escapist addiction were more likely to spend more time on TikTok during the day and open TikTok more frequently.

Socially-rewarding self-presentation. The results found socially rewarding self-presentation (SRSP) showed both positive and negative associations with TikTok usage. However, none of these results were statistically significant, not supporting this hypothesis, and thus no conclusions can be drawn about these effects. SRSP was defined by Scherr and Wang (2021) as how users value TikTok as a tool to self-produce their own content freely and a source to receive "likes" or positive reactions from others. SRSP was found to be non-significant across the number of hours spent on TikTok and the number of times users opened TikTok, which brings a need to evaluate why this result came to be. This finding also appears inconsistent with similar motives for SMU in the context of other SMP, such as Instagram (Sheldon & Bryant, 2016).

One potential explanation could be the culture from which the sample was recruited. As Scherr and Wang's study was conducted with Chinese TikTok users, there could be underlying influences of culture that are not yet known with this particular motive for TikTok use. For example, social media users from collectivist cultures (such as China) may experience positive reactions to their content from other users they are close with, such as family or friends (Dotan & Zaphiris, 2010). Scherr and Wang also noted that instant gratification from positive feedback could also be considered similar to feelings of accomplishment (Scherr & Wang, 2021), as individuals from collectivist cultures tend to strive to build lasting relationships and a strong support network on SNS (Kim et al., 2011). Individualistic TikTok users, on the other hand, might be more motivated to be more self-expressive regardless of the audience (Deng et al., 2023). From a methodological perspective, SRSP may not have been a significant predictor for TikTok use because the motive itself could be considered too broad. Scherr & Wang described SRSP as a means for creativity, self-expression, positive reactions from others, and social rewards.

However, all of these elements in SRSP may not be associated with significant TikTok usage simultaneously but separately. For some, self-expression may be a predictor (Shao & Lee, 2020), but for others, it could be the desire for social rewards (Meng & Leung, 2021). This could also be linked to how TikTok users score in personality traits in regard to this motive. For example, female users who score high in extraversion or low in neuroticism could be more likely to partake in social interactions and seek positive validation or encouragement on TikTok. Perhaps future research could emphasise usage motivated by SRSP and examine the different motives within SRSP in more depth. Furthermore, SRSP may not be as relevant of a motive for use for users who prefer watching content over creating content, in which SRSP may not appear to play a role in the amount of time users spend on TikTok or how often users open TikTok.

Trendiness. Hierarchical regression results found trendiness to be a non-significant predictor across all outcome variables, thus not supporting this hypothesis, and no conclusions can be drawn about its influence on TikTok usage behaviour. Given TikTok's widespread popularity (Dixon, 2024b), it is notable that trendiness did not significantly predict usage in a UK and USA sample.

However, upon closer inspection of the construct of trendiness in the measure used in the present study, it becomes apparent that only one of the question items directly refers to popularity: '*I use TikTok because... Everybody else is using it*'. The other items refer to using TikTok because it is '*cool'*, '*exhilarating'* or '*exciting'*, which consider perceived innovativeness of TikTok and how it seen as a modern or innovative SMP. Therefore, the broader interpretation of trendiness may not fully capture user motivations related to popularity or social conformity in SMU. Additionally, since TikTok is considered a new and unique SMP by some (Syrjälä, 2024), the perceived trendiness of the app may vary by age, further explaining the non-significant result while taking into account the present study's diverse age range (18-68).

So, trendiness may not be a significant motive reflected by the entire sample but, if compared by age, may have yielded different results. While an interaction analysis, such as age x trendiness, could have explored this further, such analyses were beyond the scope of the present study, which focused primarily on main effects. Future research could build on this impact of further analysis and investigate whether age moderates the relationship between trendiness and TikTok use, particularly given the present study's age range. Further research could also explore the popularity and trendiness of TikTok, compare motives across age groups, and examine similar or different patterns found in other visual-based SMP, such as Instagram (Sheldon & Bryant, 2016).

Also, as TikTok faces political scrutiny and ban legislation, as discussed in Chapter 1, users who search for political or news content on TikTok may not be concerned with current trends or what is popular. Another element of TikTok which may be more significant with Western users that was not explored in Scherr and Wang's measure is the importance of being popular on TikTok. For example, as part of collectivist cultures, Chinese TikTok users tend to have a smaller but stronger online social network (Lu & Wan, 2018). However, Western users might be more motivated by a desire for fame, popularity, and gaining as many followers as possible. So, trendiness as a motive for TikTok use may be important to measure longitudinally. Over time, the perceived trendiness and popularity of TikTok could be prone to change as trends, types of content, and app features also change (Mclaughlin & Stephens, 2019). However, as trends and elements of SMP change, younger users in particular who score higher in personality traits such as openness or extraversion, may be more inclined to increase their TikTok usage from a desire to experience something new or different.

Escapist addiction. Results found escapist addiction to be a significant predictor across all outcome variables, except for the number of hours spent on TikTok during night-time, therefore partially supporting the hypothesis. These findings indicate that those who scored higher in escapist addiction spent more time on TikTok and opened the app more frequently. This supports previous findings, which also found escapism to strongly predict TikTok usage (Meng & Leung, 2021; Omar & Dequan, 2020). As people from individualistic countries have already been found to use social media to escape the pressures of everyday life (Deng et al., 2023), the present study's findings can now contribute to the idea of escaping reality as one of the most relevant motives for using TikTok. Interestingly, this motive was found to be significant in the current sample (UK and USA users) and in past research comprising Chinese users, which could have implications for future cross-cultural research if this motive continues to be significant. Regarding the number of hours spent on TikTok during day-time, escapist addiction as a significant predictor could also be explained by procrastination.

As the present study's sample comprises students and working adults, both of these groups could be more inclined to use TikTok as a way to kill time by procrastinating or escaping day-to-day responsibilities (Alblwi et al., 2021; Brailovskaia et al., 2020; Nong et al., 2023). However, this could also be the case with those who are unemployed, who may want to escape boredom or find a way to pass the time. Procrastinating and escaping through SMU has already been noted in student or young adult populations, and this could also be connected to how frequently users open TikTok. Gen Z adults were found to significantly open TikTok more frequently than those in older generations (see Section 4.1.2.), which could be associated with escapism as a motive.

As discussed in Chapter 2, TikTok has been shown to have numerous benefits for mental health and well-being (Campana, 2022; Dong & Xie, 2022). With this in mind, younger adults, in particular, could be opening TikTok more frequently, almost habitually, as they know TikTok's algorithm will provide them with content they enjoy, help them escape, and have some leisure time (Vaterlaus & Winter, 2021). This could also be associated with younger users who score high in neuroticism. As being high in neuroticism could show the user experiencing feelings of self-doubt or anxiety, these traits could be associated with escapist addiction under the assumption that their online world or interactions are safer or more comforting than those offline. For example, some users could seek new content from their favourite type of content or creator, new updates in their community (e.g., BookTok), or something funny to improve their mood or achieve emotional relief.

Novelty. Finally, results found novelty to be a non-significant predictor of TikTok usage across all outcome variables, not supporting this hypothesis. Although some coefficients were negative, novelty did not significantly predict any of the outcome variables, so no conclusions can be drawn about its relationship with TikTok use. Scherr and Wang found that novelty was the most relevant motive for TikTok use, particularly at night-time. However, as with trendiness, novelty was not found to be significant at any time of the week. This could be because, like trendiness, discovering new things on TikTok may not have been a relevant motive for all participants.

For example, TikTok's algorithm is designed to figure out the users' likes and dislikes (Bhandari & Bimo, 2020). As a result, similar content may appear, thus not showing the user anything new (Scherr & Wang, 2021). For some users, this could lead to boredom; for others, they may not have the desire to see anything new. For example, users who are part of a BookTok community may grow accustomed to seeing only book-related TikTok content, or content creators who are a part of the DogTok community are used to seeing content about other users' dogs. So, there could be a lesser chance of the algorithm showing the user something new. Furthermore, it has been argued that social media users from individualistic cultures are more likely to use social media for information-seeking or escaping from real-life difficulties (Deng et al., 2023). This could also have been relevant for this study's sample, as users of an older age may be less interested in the novelty of TikTok and are seeking information or wish to kill time, as discussed in Chapter 1. Although age and motivation data were collected, this study did not conduct further subgroup or interaction analyses due to the focus on broader predictive relationships and main effects. Future research could benefit from considering conducting this analysis and explore whether age moderates the relationship between novelty-seeking and TikTok use, especially considering generational differences in engagement on SMP.

5.2. Theoretical Implications

The present study's findings contribute to past research employing U&G theory to illustrate the importance of personality traits such as extraversion or neuroticism, which significantly influence the duration and intensity of TikTok usage, thus expanding U&G theory's applications to recent SMP such as TikTok. For example, as Western TikTok users, particularly younger users, are more open to self-expression on TikTok (Scherr & Wang, 2021), being open to new experiences could be applied to more in-depth measures of SMU, such as comparing active and passive use, content preferences, and why users may choose to either watch or create content. Findings from this study also uncovered similarities and differences between Scherr and Wang's (2021) Motives for TikTok Use applied to a Western sample and the significance of appropriate measures for SMU and their relevance to specific cultures. For instance, as the duration of TikTok usage is higher in younger users, the number of times users open TikTok also could be associated with age. Also, how frequently users open TikTok does not appear to be a common measure when exploring usage. Conducting cross-cultural comparisons could provide further insight into habitual and, if observed, potentially excessive or problematic TikTok usage.

Furthermore, as new motivations for TikTok use have been uncovered in recent research, it is also important to consider culturally appropriate motives for use. For example, SRSP was considered a significant motive for Chinese users, but some motives may be more relevant to Western, such as USA or UK, users. Some possible motives could include earning money from content, as content creators and influencers are able to use TikTok as a source of income (Tanachot, 2021). However, it is important to acknowledge that the present study and the measure used for motives behind TikTok use did not include several motivations identified in prior research and discussed throughout Section 2, such as a desire for fame (Batool, 2021), information seeking (Falgoust et al., 2022), community building (Cleofas et al., 2022), self-expression (Shao & Lee, 2020), or to earn an income (Tanachot, 2021). As new motivations for TikTok use emerge, it becomes more important to consider how these motivations may differ across user communities and cultures. While existing scales, such as those developed by Scherr and Wang (2021), have identified relevant motivations such as self-presentation and escapism, they may not be able to fully reflect all motives for use of the platform. In, particular, this measure was designed for Chinese users and is unable to consider Western culture or other cultures outside China and how they use TikTok.

For example, SRSP was found to be a significant predictor of TikTok use amongst Chinese users in Scherr and Wang's (2021) study, which may reflect the influence of collectivistic cultural values, such as social approval (Triandis, 1995). On the other hand, Western users may be more driven by motivations more linked to individualistic cultures, such as fame-seeking (Batool, 2021), monetisation (Tanachot, 2021), or creative self-expression (Shao & Lee, 2020). The previously mentioned studies have found that these motives, including others not mentioned here, are becoming increasingly relevant in understanding TikTok user behaviour, and may also have relevance to specific TikTok subcultures or communities, such as BookTok

(Merga, 2021). So, the exclusion of these motivations from the present study does raise concerns around cultural validity and the relevance of pre-existing measures.

Omitting these motivations also limits the generalisability and predictive power of current motivation scales including, but not limited to, Scherr and Wang's (2021) in the current study. For example, TikTok users who create content to earn an income or develop a brand may be poorly represented in analyses based on older U&G measures. Similarly, failing to take into account motivation such as community building or self-expression could underestimate TikTok's impact on users from a psychological and social perspective. Therefore, these limitations are relevant when exploring how motivations can relate to other forms of TikTok use, such as problematic use, or user well-being or engagement behaviours. Future research may benefit from the development of a comprehensive and up-to-date scale that will capture the many evolving motivations for TikTok use, which could then be tailored to specific cultures, subcultures, or online communities. This could involve both qualitative and quantitative methods to explore underrepresented motives across cultures for a more nuanced understanding of TikTok use and its psychological implications.

Another possible motive could be similar to escapism but characterised as using TikTok out of habit. As social media is a constant presence in day-to-day living (Attrill-Smith et al., 2019), some habits involving smartphone use have emerged, such as checking your phone first thing in the morning when you wake up. Similar habits could be associated with TikTok use, such as looking regularly for new content or checking how many likes your content receives. However, it is necessary not to overlook how problematic or excessive TikTok usage could also result from increased usage. Researchers should take caution before determining higher usage to be problematic, as underlying individual differences could also play a role. For example, when using TikTok for income purposes, it is necessary for future research to consider the significance of interesting outliers in data when recording usage (Thériault et al., 2024). Extreme quantities of usage may not be something to be discarded from the dataset but as a point of theoretical interest. For example, suppose someone spends more time on TikTok to create content, make connections, and network as part of their job as a creator. In that case, their usage may appear excessive compared to the rest of the sample. TikTok may also not be the only tool used by content creators; CapCut, an editing tool also owned by ByteDance, is a popular tool for creators to edit content and directly upload it to TikTok (Herman, 2023). As such, their collective usage could also be explained by the amount of time they spend on CapCut to edit their content, which was not recorded in the present study.

Also, the present study considered one week of usage, which may only partially reflect TikTok usage over time. For instance, if a student is stressed while revising for an exam and spends time on TikTok to procrastinate or simultaneously to their studies (Lau, 2017; Mekler, 2021), their usage may differ when they are not studying for exams. Some stressors users may experience could also cause their usage to fluctuate. For instance, when using TikTok, users' 'For You' page, shop, and video editing features could be used to assess the underlying usage purpose, such as for passive scrolling, purchasing products used in videos, or content creation, respectively. Understanding the purpose of SMU should be measured objectively by utilising the unique features of the platform itself (Alshakhsi et al., 2022). The importance of employing longitudinal studies is later discussed in Section 5.5.

5.3. Practical Implications

The results of this study also have some practical implications, with the connection between personality and TikTok usage could have implications for marketing practitioners. For example, understanding that younger and open-to-experience individuals use TikTok and open TikTok more frequently can inform targeted advertising strategies. As younger individuals are more likely to use social media for seeking information (Matsa, 2023; Smith, 2023), research in marketing through social media could show greater effectiveness of using visual SMP, such as

TikTok or Instagram, for marketing purposes. Marketing strategies could also benefit from TikTok users who are more self-expressive and extroverted with many followers. These users may or may not be content creators or influencers; however, users with a large network would be a primary group for marketing practitioners to collaborate with or investigate further. Also, as users in the current sample showed significant relationships between TikTok usage and scoring high in extraversion and neuroticism, marketers could also consider TikTok as a platform designed for self-expression, emotional regulation and social communities. As TikTok communities emphasise the importance of togetherness, a sense of belonging and finding like-minded individuals (Dezuanni et al., 2022; Nagy, 2022), these communities could be detrimental to new products and efficiently targeting suitable audiences. For example, BookTok communities have impacted the sales of old and new literature due to content about genre discussions, comedy sketches, and sharing reviews or recommendations going viral (Dahlgren & Enshagen, 2023; Flood, 2021).

Some features of TikTok are also unique to the platform's commercial tactics and promote products through electronic word-of-mouth (e-WOM, Andon & Annuar, 2023), such as through the TikTok shop. So, using TikTok specifically for these purposes may be most effective as marketing researchers can observe potential customers and consumer behaviour directly through the TikTok shop and more comprehensive details on customer interactions in an online environment. Furthermore, as those in the present study who are more open to experience showed increased TikTok usage, marketers could classify this group of potential customers and analyse their consumer behaviour. Moreover, by using a TikTok environment, marketers can efficiently estimate the activity of customers in various networks by analysing other users' followers or specific groups, such as those in BookTok communities. These suggested methods for marketing practitioners could also provide a useful structure for researchers in order to keep up with TikTok's ever-changing features, popular content, and user interactions within and across cultures (Alhabash & Ma, 2017; Dong & Xie, 2022; Wang, 2022).

When considering the most significant motive identified in the present study, escapist addiction, mental health and well-being providers could also have practical implications in Western populations. Problematic use, as discussed in Section 2, refers to patterns of SMU that could affect physical or emotional wellbeing, or social relationships (Ahmed et al., 2022; Ali et al., 2015; Gustafsson et al., 2010; Udayanga, 2023). Problematic use is often characterized as excessive or compulsive, with users experiencing a lack of self-control and reliance on the app as a means of coping (Yang, 2023). Since the COVID-19 pandemic, TikTok has become a diverse online environment for seeking mental health support, information, or advice (Basch et al., 2022; Campana, 2022; Dong & Xie, 2022), but it also had the potential to foster unhealthy escapist behaviour during periods of social isolation (Li, Sun, et al., 2021; Siste et al., 2020). As none of the other motives for use were found to be significant in the present study, these findings could recommend that policymakers should delve into the motive of escapism in Western populations to try and identify from what TikTok users are escaping. From this, features to regulate features that may contribute to problematic SMU, such as mindless scrolling or algorithm-driven content (Ebrahim, 2023; Li, 2023), could be introduced.

The measure used in this study comprised statements about taking a break, avoiding unpleasant things in their life, using TikTok because they cannot stop, passing the time, or not wanting to do something else. Each of these statements could have implications for the user's mental health and well-being, which could provide richer insight into how mental health and well-being providers approach and intervene with social media users and their health. These motives behind using TikTok, if reaching the threshold to be considered problematic, could signal underlying concerns such as mental health conditions like anxiety or depression (Lin et al., 2016; Ramsden & Talbot, 2024). As such, mental health professionals should be aware of

TikTok's highly engaging and algorithmically curated content and how this may lead to problematic, or eventually addictive, online usage or behaviour, resulting in greater difficulty in breaking these patterns. This approach could also be combined with practical implications of understanding digital and social media fatigue and how the user's online behaviour or overall usage may change, which could affect their lives online and offline (Appel et al., 2019; Zhang et al., 2020). Practitioners could also develop target intervention that address feeling of escapism and promote digital wellbeing, such designing programs which encourage mindful content consumption, time management strategies, or propose therapeutic approaches to cope beyond using social media.

5.4. Strengths

The present study displayed several strengths. Previous studies into SMU relied on self-reported usage (Lin et al., 2015; Mahalingham et al., 2023; Parry et al., 2021), but face difficulties and biases on how self-reported measures are utilised (Ernala et al., 2020; Sewall et al., 2020). The present study was based on comparing self-reports and objective data to examine potential differences in self-reporting SMU and improve methodological approaches in future research. Using objective measures also lessened the risk of recall or social desirability bias, and the hours of day- and night-time were characterised from the TikTok app privacy settings to ensure consistency when comparing across participants. Using hierarchical regression was also most suitable for comparing the multiple groups of predictors as it allows to control for demographic variables, such as age or gender, before exploring the influence of other variables, such as personality (Cramer, 2003).

Another key strength of this study was the use of two distinct outcomes measures: hours spent on TikTok and the number of times the app was opened. By exploring TikTok use with multiple measures, this study provides a comprehensive understanding of user engagement and behaviour. Also, employing a dual-measure approach allows for a more nuanced analysis of how demographic factors, personality traits, and motives for use relate to different measures of SMU, thus increasing the robustness and interpretive depth of the findings. Furthermore, testing hypotheses across both measures of SMU ensures that conclusions about predictors of TikTok use are not dependent on a single measure, enhancing confidence in the results of this study,

This study also expands on Scherr and Wang's use of motives for TikTok use to a Western sample after their investigation into an Eastern sample from China. Recruiting TikTok users from the UK and USA expands upon past research into TikTok in Asian (e.g., Dong & Xie, 2023; Su et al., 2021; Yao et al., 2023) or European cultures (e.g., Bossen & Kottasz, 2020; Dias & Duarte, 2022; Şot, 2022), enhances the applicability for future TikTok research from a cross-cultural perspective. The current study's sample also comprised multiple age groups to expand upon current research which support the argument that young people typically use social media, and so only young people are explored (Alhabash & Ma, 2017; Deng et al., 2023; Kıran & Demirçeviren, 2021). This study aimed to consider age groups beyond adolescents, students and young adults, and consider individuals who may still use social media, regardless of their SMU being lesser than those younger than them. Despite being less accustomed to social media, adults or older individuals may have unique motives for SMU (Auxier & Anderson, 2021; Chao et al., 2023; Qiu, 2022) based on individual differences, lifestyle, or health and well-being. For instance, elderly users may connect with family and friends on TikTok due to limited physical mobility, or adults in the Millennial generation may use TikTok for community building or for working as a content creator.

The study also had some strengths regarding the online survey, the measures used, and its distribution. Time zone differences between the UK and USA were accounted for during survey distribution, aiming to make participation feasible across both countries. This consideration when planning the data collection stage aimed to ensure participants could reasonably access the study during their local daytime hours, thus improving response rates and reducing the likelihood of being unable to participate due to inconvenient timing. The BFI-10 has also been found to be a strong and reliable measure in WEIRD countries, with good structural validity, test-retest reliability, and consistency (Rammstedt et al., 2012; Steyn & Ndofirepi, 2022). The decision to use the 10-item measure was also beneficial for the study as it was a less time-consuming measure for personality, and so participants were less likely to lose interest or leave the survey incomplete. Using Scherr and Wang's (2021) Motives for TikTok Use was intended to build upon their findings from a Chinese sample and apply their measure to other cultures. The motives from this measure revealed interesting findings, as only one motive for use was found to be significant across the sample (escapist addiction). As the measure's reliability values were found to be satisfactory as reported in Section 3.3.1., it was expected all motives would be significant predictors of TikTok usage. However, this was not the case, which could suggest that the motives used in this measure which were found to be significant with Chinese users, may not be as relevant to UK or USA TikTok users.

5.5. Limitations

The current study is also subject to some limitations. For instance, the study's sample comprised UK and USA citizens, but these countries have extreme differences in population. Having recruited 100 participants from the USA does not appear generalisable to the entirety of the country. Future research may benefit from investigating solely the USA and recruiting from as many states as possible, particularly when considering debates surrounding TikTok bans in the USA. The sample size is also limited in applicability to the UK, and more research into TikTok in the UK is recommended. Furthermore, recruiting through Sona Systems limits recruitment to students from one university, and the present study's findings may not be applicable to students at other UK universities. While Prolific had fewer recruitment restrictions from both countries, future research could employ more specific criteria for participation, such as not being a student and a citizen of a specific state or region in the USA or UK, respectively.

Also, utilising convenience sampling limits the generalisability of the sample as a whole (Falgoust et al., 2022). Future investigations should consider employing stratified random sampling, which would allow for the deliberate inclusion of chosen subgroups – such as participants from multiple states in the USA, from various regions in the UK, and different educational backgrounds from both countries – to improve the representativeness and generalisability of the findings. Time constraints may also have played a part in the lack of USA participants compared to UK participants. Despite efforts to account for time zone differences (as mentioned previously in Section 5.4.), the timing of the study being published on Prolific became a limitation. Due to the zone time difference between the UK and the USA, potential USA participants living across the country's many time zones – four primary time zones between the east and west coasts and two additional time zones used by Alaska and Hawaii – compared to only one time zone used in the UK. Consequently, recruitment announcements made during UK daytime hours may have reached many U.S. participants during the night or early morning, reducing their likelihood of viewing or responding to the study invitation in time. This timing mismatch likely contributed to the lower representation of USA participants (100 compared to 262 from the UK.

Another limitation was the age and employment status of the participants. The number of participants over the age of 28 (Millennial) was less compared to those of a younger age (Gen Z), so it is not easy to generalise this study's findings. The majority of the sample comprised users who were students (full-time or part-time) or employed full-time, but users who may fit multiple employment statuses (such as full-time students who also work part-time) are not acknowledged within this sample. For those who are employed, the amount of time spent on TikTok may also be for work purposes, such as creating content for a business account (Johnson et al., 2022; Nair et al., 2022), and so qualitative or mixed methods approaches may be more suitable for future studies. Similarly, for users currently in education, the amount of time they spend on TikTok could be associated with a desire for specific content, such as educational content, which has become more prevalent since the COVID-19 pandemic. Using TikTok for business purposes could be an interesting direction, as this study did not go beyond asking if participants used TikTok for business or not. Also, for participants who stated having more than one TikTok account, it may be logical to assume that multiple accounts could be clarified as having a personal and business or professional account, where usage could vary between accounts depending on their purpose. From this, perhaps further investigation into content creators and influencing as a profession could bring an interesting perspective on TikTok and how it can be used as a source of income.

Another limitation of this study to reflect upon is from each hypothesis being tested across two separate outcome measures, which increased the number of statistical tests conducted in the analysis phase. While this approach provided a broader perspective on SMU and user engagement, this may also increase the risk of Type I errors and complicate the interpretation of the results. Consequently, some non-significant findings may have been influenced by how the tests were conducted, rather than showing there is no relationship. Future research could consider consolidating outcome measures or applying appropriate statistical corrections to account for multiple testing, and thus reduce the potential risk of misleading findings.

The study's methodology also revealed some limitations which could be improved upon by conducting longitudinal studies. As the current study examined TikTok use at a single point in time, the present findings do not claim that there is necessarily a causal relationship between variables. While the time spent on TikTok is a useful measure in conceptualising SMU, other elements which are associated with usage could also be employed in longitudinal studies, such as the types of content users watch, if they prefer to watch or create content, or both, and active or passive SMU. Other SMP which would be relevant to TikTok usage should also be considered, such as how long or why people use CapCut to edit their videos. Perhaps, future research could investigate these platforms simultaneously and how users who primarily create content may have varying usage to those who passively watch content. It may also be prudent to consider non-TikTok users in future research, as this study is limited to a single SMP and is not representative of social media usage collectively in UK and USA populations.

Also, as the current study employed 5-point Likert scales, this may restrict complex ideas, such as why an individual may use a specific SMP. For example, using a 5-point scale with 3 in the centre of the scale, it is not clear if choosing 3 as a response means that the participant has no opinion or is undecided about their response (Coolican, 2024, p.227). Some researchers argue that the midpoint in a Likert scale question may reduce data quality or suggest satisficing behaviour, a response strategy used by participants to give an adequate or satisfactory answer to a question with minimal cognitive effort. (Johns, 2005; Krosnick, 1991). On the other hand, some defend the notion of a neutral option as it is important to avoid forcing participant into expressing a view or opinion that they do not have (Chyung et al., 2017). For future research, a more elaborated scale over longitudinal studies or using mixed-method responses may yield more insightful results when measuring user motivation (Alshakhsi et al., 2022). For example, even-numbered Likert scales could be used in longitudinal studies to prompt more decisive responses over time, or mixed-methods studies could employ follow-up qualitative survey items to allow the participant to clarify their intent behind a neutral choice in an odd-numbered Likert scale.

5.6. Conclusion

In conclusion, this study highlights the importance of demographic factors, personality traits, and user motivation in predicting TikTok usage. The present study's findings offer insight for both theoretical and practical applications in the constantly changing field of social media research. Future research should continue to explore the time spent or how often users open

TikTok from a longitudinal perspective to gain an understanding of deeper psychological influences of TikTok usage over time. Also, due to TikTok's diverse array of content and fluctuating popularity due to political and personal opinions of Western individuals, exploring beyond the quantity of usage into thought, feelings, and behaviour of TikTok users could yield much needed insight into the mind of the users themselves. Furthermore, examining other emerging motives for TikTok use in Western cultures could provide a more comprehensive understanding of the relationship between TikTok usage and behaviour across cultures.

References

Aalberg, T., Van Aelst, P., & Curran, J. (2012). Media systems and the political information environment: A cross-national comparison. In *How Media Inform Democracy (1st ed.* (pp. 33–49). Routledge.

Aguinis, H., Gottfredson, R. K., & Joo, H. (2013). Best-Practice recommendations for defining, identifying, and handling outliers. *Organizational Research Methods*, *16*(2), 270–301. https://doi.org/10.1177/1094428112470848

Ahlse, J., Nilsson, F., & Sandström, N. (2020). *It's time to TikTok: Exploring Generation Z's motivations to participate in #Challenges* [Bachelor Thesis]. https://www.diva-portal.org/smash/record.jsf?pid=diva2%3A1434091&dswid=-6633

Ahmed, S., Mishra, A., Akter, R., Shah, Md. H., & Sadia, A. A. (2022). Smartphone addiction and its impact on musculoskeletal pain in neck, shoulder, elbow, and hand among college going students: A cross-sectional study. *Bulletin of Faculty of Physical Therapy*, *27*(1). https://doi.org/10.1186/s43161-021-00067-3

Akhtar, N., & Islam, T. (2023). Unveiling the predictors and outcomes of TikTok addiction: the moderating role of parasocial relationships. *Kybernetes*. https://doi.org/10.1108/k-04-2022-0551

Akram, W., & Kumar, R. (2017). A study on positive and negative effects of social media on society. *International Journal of Computer Sciences and Engineering*, *5*(10), 351–354. Research Gate. https://doi.org/10.26438/ijcse/v5i10.351354

Alan, A. K., & Kabadayı, E. T. (2016). The Effect of Personal Factors on Social Media Usage of Young Consumers. *Procedia - Social and Behavioral Sciences*, *235*, 595–602. https://doi.org/10.1016/j.sbspro.2016.11.086

Alavi, S. S., Ferdosi, M., Jannatifard, F., Eslami, M., Alaghemandan, H., & Setare, M. (2012). Behavioral addiction versus substance addiction: Correspondence of psychiatric and psychological views. *International Journal of Preventive Medicine*, *3*(4), 290–294. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3354400/

Alblwi, A., McAlaney, J., Al Thani, D. A. S., Phalp, K., & Ali, R. (2021). Procrastination on social media: predictors of types, triggers and acceptance of countermeasures. *Social Network Analysis and Mining*, *11*(1). https://doi.org/10.1007/s13278-021-00727-1

Alblwi, A., Stefanidis, A., Phalp, K., & Ali, R. (2019). Procrastination on Social Networks: Types and Triggers. *2019 6th International Conference on Behavioral, Economic and Socio-Cultural Computing (BESC)*, 1–7. https://doi.org/10.1109/besc48373.2019.8963036

Alhabash, S., & Ma, M. (2017). A tale of four platforms: Motivations and uses of Facebook, Twitter, Instagram, and Snapchat among college students? *Social Media + Society*, *3*(1), 1–13. https://doi.org/10.1177/2056305117691544

Alhabash, S., & McAlister, A. R. (2014). Redefining virality in less broad strokes: Predicting viral behavioral intentions from motivations and uses of Facebook and Twitter. *New Media & Society*, *17*(8), 1317–1339. https://doi.org/10.1177/1461444814523726

Ali, R., Jiang, N., Phalp, K., Muir, S., & McAlaney, J. (2015). The emerging requirement for digital addiction labels. *Requirements Engineering: Foundation for Software Quality*, *9013*, 198–213. https://doi.org/10.1007/978-3-319-16101-3 13

Allahverdi, F. Z. (2022). Relationship between perceived social media addiction and social media applications frequency usage among university students. *Psychology in the Schools*, *59*(6). https://doi.org/10.1002/pits.22662

Allas, T., Canal, M., & Hunt, V. (2020). *COVID-19 in the United Kingdom: Assessing jobs at risk and the impact on people and places*. McKinsey & Company.

Allport, G. W. (1937). *Personality: A psychological interpretation*. Holt. https://psycnet.apa.org/record/1938-01964-000

Almoallim, S., & Sas, C. (2023, August). Patterns of Meaningful and Meaningless Smartphone Use: A Diary Study. *36th International BCS Human-Computer Interaction Conference*. https://www.researchgate.net/publication/377242089 Patterns of Meaningful and Meaningless Smartphone Use A Diary Study

Almourad, B., McAlaney, J., Skinner, T., Pleva, M., & Ali, R. (2020). Defining digital addiction: Key features from the literature. *Psihologija*, *53*(3), 237–253. https://doi.org/10.2298/psi191029017a

Alruwaili, T. O. M. (2017). *Self identity and community through social media: The experience of Saudi female international college students in the United States* [PhD Dissertation]. https://digscholarship.unco.edu/dissertations/401/

Alshakhsi, S., Chemnad, K., Almourad, M. B., Altuwairiqi, M., McAlaney, J., & Ali, R. (2022). Problematic internet usage: the impact of objectively recoded and categorized usage time, emotional intelligence components and subjective happiness about usage. *Heliyon*, *8*(10), e11055. https://doi.org/10.1016/j.heliyon.2022.e11055

Althubaiti, A. (2016). Information bias in health research: Definition, pitfalls, and adjustment methods. *Journal of Multidisciplinary Healthcare*, *9*(1), 211–217. https://doi.org/10.2147%2FJMDH.S104807

American Psychiatric Association. (2013). *Diagnostic and statistical manual of mental disorders* (5th ed.). American Psychiatric Association.

Amichai-Hamburger, Y., & Vinitzky, G. (2010). Social network use and personality. *Computers in Human Behavior*, *26*(6), 1289–1295. https://doi.org/10.1016/j.chb.2010.03.018

Amichai-Hamburger, Y., Wainapel, G., & Fox, S. (2002). "On the Internet No One Knows I'm an Introvert": Extroversion, Neuroticism, and Internet Interaction. *CyberPsychology & Behavior*, *5*(2), 125–128. https://doi.org/10.1089/109493102753770507

Anastasi, A., & Urbina, S. (1997). *Psychological testing* (7th ed.). Pearson. https://psycnet.apa.org/record/1998-07223-000

Anderson, K. E. (2017). Getting acquainted with social networks and apps: Social Media in 2017. *Library Hi Tech News*, *34*(10), 1–6. https://doi.org/10.1108/lhtn-10-2017-0073

Anderson, K. E. (2018). Getting acquainted with social networks and apps: Streaming video games on Twitch.tv. *Library Hi Tech News*, *35*(9), 7–10. https://doi.org/10.1108/lhtn-08-2018-0054

Anderson, K. E. (2020). Getting acquainted with social networks and apps: it is time to talk about TikTok. *Library Hi Tech News*, *37*(4), 7–12. https://doi.org/10.1108/lhtn-01-2020-0001

Anderson, K. E. (2021). Getting acquainted with social networks and apps: talking about TikTok. *Library Hi Tech News*, *38*(6), 1–6. http://dx.doi.org/10.1108/LHTN-10-2021-0077

Andon, N. S., & Annuar, S. N. S. (2023). The adaptation of social media marketing activities in s-commerce: TikTok Shop. *Information Management and Business Review*, *15*(1(I)SI), 176–183. https://doi.org/10.22610/imbr.v15i1(I)SI.3404

Andreassen, C. S. (2015). Online Social Network Site Addiction: A Comprehensive Review. *Current Addiction Reports*, *2*(2), 175–184. https://doi.org/10.1007/s40429-015-0056-9

Andreassen, C. S., Pallesen, S., & Griffiths, M. D. (2017). The relationship between addictive use of social media, narcissism, and self-esteem: Findings from a large national survey. *Addictive Behaviors*, *64*(64), 287–293. https://doi.org/10.1016/j.addbeh.2016.03.006

Andrews, S., Ellis, D. A., Shaw, H., & Piwek, L. (2015). Beyond self-report: Tools to compare estimated and real-world smartphone use. *PLOS ONE*, *10*(10), e0139004. https://doi.org/10.1371/journal.pone.0139004

Ang, C. (2022, May 12). *The Top Downloaded Apps in 2022*. Visual Capitalist. https://www.visualcapitalist.com/top-downloaded-apps-2022/

Anguiano, D. (2023, May 17). Montana becomes first US state to ban TikTok. *The Guardian*. https://www.theguardian.com/us-news/2023/may/17/tiktok-ban-montana#:~:text=Montana%20has%20became%20the%20first

APA Dictionary of Psychology. (2025). *Algorithm*. American Psychological Association. Retrieved April 17, 2023, from https://dictionary.apa.org/algorithm

Appel, M., Marker, C., & Gnambs, T. (2019). Are social media ruining our lives? A review of meta-analytic evidence. *Review of General Psychology*, *24*(1), 108926801988089. https://doi.org/10.1177/1089268019880891

Araujo, T., Wonneberger, A., Neijens, P., & de Vreese, C. (2017). How much time do you spend online? Understanding and improving the accuracy of self-reported measures of internet use. *Communication Methods and Measures*, *11*(3), 173–190. https://doi.org/10.1080/19312458.2017.1317337

Arriagada, A., & Ibáñez, F. (2020). "You Need At Least One Picture Daily, if Not, You're Dead": Content Creators and Platform Evolution in the Social Media Ecology. *Social Media + Society*, *6*(3), 205630512094462. https://doi.org/10.1177/2056305120944624

Attrill-Smith, A., Fullwood, C., Keep, M., & Kuss, D. J. (2019). *The Oxford Handbook of Cyberpsychology*. Oxford University Press.

Auxier, B., & Anderson, M. (2021, April 7). *Social media use in 2021*. Pew Research Center; Pew Research Center. https://www.pewresearch.org/internet/2021/04/07/social-media-use-in-2021/

Bahagia, B., Wibowo, R., Muniroh, L., Wahid, A. A., Rizkal, R., Noor, Z. M., & Karim, A. (2022). The Drawbacks and Advantages of TikTok in Student Amid Pandemic Covid-19. *Jurnal Basicedu*, *6*(3), 5302–5310. https://doi.org/10.31004/basicedu.v6i3.2459

Baixauli, E. (2017). Happiness: Role of dopamine and serotonin on mood and negative emotions. *Emergency Medicine: Open Access*, *07*(02). https://doi.org/10.4172/2165-7548.1000350

Balcı, Ş., & Karaman, S. Y. (2020). Social media usage, self-presentation, narcissism, and self-esteem as predictors of Instagram addiction: An intercultural comparison. *Erciyes İletişim Dergisi*, *7*(2), 1213–1239. https://doi.org/10.17680/erciyesiletisim.719895

Baltacı, Ö. (2019). The Predictive Relationships between the Social Media Addiction and Social Anxiety, Loneliness, and Happiness. *International Journal of Progressive Education*, *15*(4), 73–82. https://doi.org/10.29329/ijpe.2019.203.6

Bányai, F., Zsila, Á., Király, O., Maraz, A., Elekes, Z., Griffiths, M. D., Andreassen, C. S., & Demetrovics, Z. (2017). Problematic social media use: Results from a large-scale nationally representative adolescent sample. *PLOS ONE*, *12*(1), 1–13. https://doi.org/10.1371/journal.pone.0169839

Barnard, M., Kerr, J., Kinsella, R., Orford, J., Reith, G., & Wardle, H. (2013). Exploring the relationship between gambling, debt and financial management in Britain. *International Gambling Studies*, *14*(1), 82–95. https://doi.org/10.1080/14459795.2013.842606

Barnes, D. (2015, March 5). *Social Media and the Ability to "Be."* HuffPost. https://www.huffpost.com/entry/social-media-and-the-abil b 6805530

Barrick, M., & Mount, M. (1991). The Big Five personality dimensions and job performance: A meta-analysis. *Personnel Psychology*, *44*(1), 1–26. https://doi.org/10.1111/j.1744-6570.1991.tb00688.x

Barry, C. T., Malia-Isabel Berbano, Anderson, A., & Levy, S. (2024). Psychology Tok: Use of TikTok, mood, and self-perception in a sample of college students. *Journal of Technology in Behavioral Science*. https://doi.org/10.1007/s41347-024-00390-1

Basch, C. H., Donelle, L., Fera, J., & Jaime, C. (2022). Deconstructing TikTok Videos on Mental Health: Cross-sectional, Descriptive Content Analysis. *JMIR Formative Research*, *6*(5), e38340. https://doi.org/10.2196/38340

Basch, C. H., Fera, J., Pellicane, A., & Basch, C. E. (2021). Handwashing videos on TikTok during the COVID-19 Pandemic: Potential for disease prevention and health promotion. *Infection, Disease & Health*, *27*(1). https://doi.org/10.1016/j.idh.2021.09.039

Basch, C. H., Hillyer, G. C., & Jaime, C. (2020). COVID-19 on TikTok: harnessing an emerging social media platform to convey important public health messages. *International Journal of Adolescent Medicine and Health*, *34*(5), 367–369. https://doi.org/10.1515/ijamh-2020-0111

Basch, C. H., Meleo-Erwin, Z., Fera, J., Jaime, C., & Basch, C. E. (2021). A global pandemic in the time of viral memes: COVID-19 vaccine misinformation and disinformation on TikTok. *Human Vaccines & Immunotherapeutics*, *17*(8), 1–5. https://doi.org/10.1080/21645515.2021.1894896

Bashir, I., Malik, A., & Mahmood, K. (2021). Social media use and information-sharing behaviour of university students. *IFLA Journal*, *47*(4), 034003522199156. https://doi.org/10.1177/0340035221991564

Batool, A. (2021). A correlational study of personality traits, self-esteem and desire for fame in TikTok makers. *Forman Journal of Social Sciences*, *01*(01), 1–32.

Baughan, A., Zhang, M. R., Rao, R., Lukoff, K., Schaadhardt, A., Butler, L. D., & Hiniker, A. (2022). “I Don’t Even Remember What I Read”: How Design Influences Dissociation on Social Media. *CHI Conference on Human Factors in Computing Systems*, 1–13. https://doi.org/10.1145/3491102.3501899

Baumeister, R. F., & Leary, M. R. (2007). The need to belong: Desire for interpersonal attachments as a fundamental human motivation. In *Interpersonal Development (1st ed.)* (p. 33). Routledge.

Bell, C., Fausset, C., Farmer, S., Nguyen, J., Harley, L., & Fain, W. B. (2013). Examining social media use among older adults. *Proceedings of the 24th ACM Conference on Hypertext and Social Media*, 158–163. https://doi.org/10.1145/2481492.2481509

Bert, F., Giacometti, M., Gualano, M. R., & Siliquini, R. (2013). Smartphones and Health Promotion: A Review of the Evidence. *Journal of Medical Systems*, *38*(1). https://doi.org/10.1007/s10916-013-9995-7

Bhandari, A., & Bimo, S. (2020). TikTok and the “Algorithmized Self”: A new model of online interaction. *AoIR Selected Papers of Internet Research*, *2020: AoIR2020*(Papers B). https://doi.org/10.5210/spir.v2020i0.11172

Bhandari, A., & Bimo, S. (2022). Why’s Everyone on TikTok Now? The Algorithmized Self and The Future of Self-Making on Social Media. *Social Media + Society*, *8*(1), 1–11. https://doi.org/10.1177/20563051221086241

Bibeva, I. (2021). *An exploration of older adults’ motivations for creating content on TikTok and the role this plays for fostering new social connections* [Master Thesis]. https://www.diva-portal.org/smash/get/diva2:1601207/FULLTEXT02

Billieux, J., Schimmenti, A., Khazaal, Y., Maurage, P., & Heeren, A. (2015). Are we overpathologizing everyday life? A tenable blueprint for behavioral addiction research. *Journal of Behavioral Addictions*, *4*(3), 119–123. https://doi.org/10.1556/2006.4.2015.009

Birney, A. (2022, May 10). *What is the maximum length for a TikTok video?* Android Authority. https://www.androidauthority.com/how-long-are-tiktok-videos-3163309/

Bishqemi, K., & Crowley, M. (2022). TikTok Vs. Instagram: Algorithm Comparison. *Journal of Student Research*, *11*(1). https://doi.org/10.47611/jsrhs.v11i1.2428

Blackwell, D., Leaman, C., Tramposch, R., Osborne, C., & Liss, M. (2017). Extraversion, neuroticism, attachment style and fear of missing out as predictors of social media use and addiction. *Personality and Individual Differences*, *116*, 69–72. https://doi.org/10.1016/j.paid.2017.04.039

Blank, G., & Lutz, C. (2017). Representativeness of social media in Great Britain: Investigating Facebook, LinkedIn, Twitter, Pinterest, Google+, and Instagram. *American Behavioral Scientist*, *61*(7), 741–756. https://doi.org/10.1177/0002764217717559

Block, J. J. (2007). Pathological computer use in the USA. *International Symposium on the Counseling and Treatment of Youth Internet Addiction*, 433.

Blumler, J. G., Katz, E., & Gurevitch, M. (1974). *The uses and gratifications approach to mass communication*. Sage Publications.

Bohn, A., Buchta, C., Hornik, K., & Mair, P. (2014). Making friends and communicating on Facebook: Implications for the access to social capital. *Social Networks*, *37*, 29–41. https://doi.org/10.1016/j.socnet.2013.11.003

Borges, N. P. (2023). *User gratifications in social media usage – The case of TikTok* [Master Dissertation]. https://repositorio.ucp.pt/handle/10400.14/41410

Bossen, C. B., & Kottasz, R. (2020). Uses and gratifications sought by pre-adolescent and adolescent TikTok consumers. *Young Consumers*, *21*(4). https://doi.org/10.1108/yc-07-2020-1186

Bourdieu, P. (1986). The forms of capital. In *Handbook of Theory and Research for the Sociology of Education* (pp. 241–258). Greenwood Press.

Bowden-Green, T., Hinds, J., & Joinson, A. (2020). How is extraversion related to social media use? A literature review. *Personality and Individual Differences*, *164*, 110040. https://doi.org/10.1016/j.paid.2020.110040

Bowe, B. J., & Wohn, D. Y. (2015). Are there generational differences? Social media use and perceived shared reality. *Proceedings of the 2015 International Conference on Social Media & Society*, 1–5. https://doi.org/10.1145/2789187.2789200

Bowman, L. L., Levine, L. E., Waite, B. M., & Gendron, M. (2010). Can students really multitask? An experimental study of instant messaging while reading. *Computers & Education*, *54*(4), 927–931. https://doi.org/10.1016/j.compedu.2009.09.024

Boyd, D. M., & Ellison, N. B. (2007). Social Network Sites: Definition, History, and Scholarship. *Journal of Computer-Mediated Communication*, *13*(1), 210–230. https://doi.org/10.1111/j.1083-6101.2007.00393.x

Boyle, S., Baez, S., Trager, B. M., & LaBrie, J. W. (2022). Systematic bias in self-reported social media use in the age of platform swinging: Implications for studying social media use in relation to adolescent health behavior. *International Journal of Environmental Research and Public Health*, *19*(16), 9847. https://doi.org/10.3390/ijerph19169847

Brailovskaia, J., Rohmann, E., Bierhoff, H.-W., & Margraf, J. (2018). The brave blue world: Facebook flow and Facebook Addiction Disorder (FAD). *PLOS ONE*, *13*(7), e0201484. https://doi.org/10.1371/journal.pone.0201484

Brailovskaia, J., Schillack, H., & Margraf, J. (2020). Tell me why are you using social media (SM)! Relationship between reasons for use of SM, SM flow, daily stress, depression, anxiety, and addictive SM use – An exploratory investigation of young adults in Germany. *Computers in Human Behavior*, *113*(106511), 106511. https://doi.org/10.1016/j.chb.2020.106511

Brailovskaia, J., Truskauskaite-Kuneviciene, I., Kazlauskas, E., & Margraf, J. (2021). The patterns of problematic social media use (SMU) and their relationship with online flow, life satisfaction, depression, anxiety and stress symptoms in Lithuania and in Germany. *Current Psychology*, *42*. https://doi.org/10.1007/s12144-021-01711-w

Brammer, S. E., Martinez, R. J., & Punyanunt-Carter, N. M. (2023). "People on TikTok aren't afraid to share stories": Examining College Students' Perceptions Regarding Self-Disclosure Behaviors on TikTok. *Studies in Media and Communication*, *11*(1), 77. https://doi.org/10.11114/smc.v11i1.5825

Brasel, S. A., & Gips, J. (2011). Media multitasking behavior: Concurrent television and computer usage. *Cyberpsychology, Behavior, and Social Networking*, *14*(9), 527–534. https://doi.org/10.1089/cyber.2010.0350

Bright, L. F., Kleiser, S. B., & Grau, S. L. (2015). Too much Facebook? An exploratory examination of social media fatigue. *Computers in Human Behavior*, *44*, 148–155. https://doi.org/10.1016/j.chb.2014.11.048

British Psychological Society. (2017). *Practice Guidelines (3rd ed.)*. https://doi.org/10.53841/bpsrep.2017.inf115

British Psychological Society. (2021a). *Code of Ethics and Conduct*. https://doi.org/10.53841/bpsrep.2021.inf94

British Psychological Society. (2021b). *Code of Human Research Ethics*. https://doi.org/10.53841/bpsrep.2021.inf180

Brooks, J., Reed, D., & Savage, B. (2016). Taking off with a pilot: the importance of testing research instruments. *Proceedings of the 15th European Conference on Research Methodology for Business and Management Studies (ECRM 2016)*, 51–59.

https://www.proquest.com/openview/1179f7e10f63e29dff2d0611c6fa88d6/1?pq-origsite=gscholar&cbl=1796413

Burnell, K., George, M. J., Kurup, A. R., Underwood, M. K., & Ackerman, R. A. (2021). Associations between self-reports and device-reports of social networking site use: An application of the truth and bias model. *Communication Methods and Measures*, *15*(2), 156–163. https://doi.org/10.1080/19312458.2021.1918654

Burrell, J., Kahn, Z., Jonas, A., & Griffin, D. (2019). When users control the algorithms: Values expressed in practices on Twitter. *Proceedings of the ACM on Human-Computer Interaction*, *3*(CSCW), 1–20. https://doi.org/10.1145/3359240

Butt, S., & Phillips, J. G. (2008). Personality and self reported mobile phone use. *Computers in Human Behavior*, *24*(2), 346–360. https://doi.org/10.1016/j.chb.2007.01.019

Campana, S. (2022). *TikTok, coronavirus, and Generation Z: How the social platform became an outlet a generation with pandemic related mental health struggles was looking for* [Bachelor of Science Thesis]. https://digitalcommons.sacredheart.edu/acadfest/2022/all/16/

Cao, Y., Chen, R. C., & Katz, A. J. (2024). Why is a small sample size not enough? *The Oncologist*, *29*(9), 761–763. https://doi.org/10.1093/oncolo/oyae162

Caponnetto, P., Lanzafame, I., Graziella Chiara Prezzavento, Abdulnaser Fakhrou, Lenzo, V., Sardella, A., Moussa, M. A., & Quattropani, M. C. (2025). Does TikTok addiction exist? A qualitative study. *Health Psychology Research*, *13*. https://doi.org/10.52965/001c.127796

Carr, C. T., & Hayes, R. A. (2015). Social Media: Defining, Developing, and Divining. *Atlantic Journal of Communication*, *23*(1), 46–65. https://doi.org/10.1080/15456870.2015.972282

Carrier, L. M., Cheever, N. A., Rosen, L. D., Benitez, S., & Chang, J. (2009). Multitasking across generations: Multitasking choices and difficulty ratings in three generations of Americans. *Computers in Human Behavior*, *25*(2), 483–489. https://doi.org/10.1016/j.chb.2008.10.012

Cash, H., D. Rae, C., H. Steel, A., & Winkler, A. (2012). Internet addiction: A brief summary of research and practice. *Current Psychiatry Reviews*, *8*(4), 292–298. https://doi.org/10.2174/157340012803520513

Cattell, R. B. (1948). Primary personality factors in the realm of objective tests. *Journal of Personality*, *16*(4), 459–486. https://doi.org/10.1111/j.1467-6494.1948.tb02301.x

Ceci, L. (2022, September 22). *TikTok Users Forecast UK 2019-2024*. Statista. https://www.statista.com/statistics/1116512/uk-tiktok-users-forecast/

Ceci, L. (2023a, January 2). *TikTok Monthly Active Users UK 2020-2022*. Statista. https://www.statista.com/statistics/1125306/tiktok-monthly-active-users-uk/

Ceci, L. (2023b, February 6). *Global TikTok user age and gender distribution 2022*. Statista. https://www.statista.com/statistics/1299771/tiktok-global-user-age-distribution/

Ceci, L. (2023c, May 12). *TikTok ban in global regions and institutions 2023*. Statista. https://www.statista.com/statistics/1381501/tiktok-ban-partial-full-global-regions/

Ceci, L. (2024a, May 13). *TikTok Use in the UK by Age 2024*. Statista. https://www.statista.com/statistics/1464776/uk-tiktok-use-by-age/

Ceci, L. (2024b, February 1). *Global TikTok user distribution by gender 2024*. Statista. https://www.statista.com/statistics/1299785/distribution-tiktok-users-gender/

Cemiloglu, D., Almourad, M. B., McAlaney, J., & Ali, R. (2022). Combatting digital addiction: Current approaches and future directions. *Technology in Society*, *68*, 101832. https://doi.org/10.1016/j.techsoc.2021.101832

Chan, V., & Allman-Farinelli, M. (2022). Young Australian Adults Prefer Video Posts for Dissemination of Nutritional Information over the Social Media Platform Instagram: A Pilot Cross-Sectional Survey. *Nutrients*, *14*(20), 4382. https://doi.org/10.3390/nu14204382

Chao, M., Lei, J., He, R., Jiang, Y., & Yang, H. (2023). TikTok use and psychosocial factors among adolescents: Comparisons of non-users, moderate users, and addictive users. *Psychiatry Research*, *325*(115247), 115247. https://doi.org/10.1016/j.psychres.2023.115247

Chen, G. M. (2011). Tweet this: A uses and gratifications perspective on how active Twitter use gratifies a need to connect with others. *Computers in Human Behavior*, *27*(2), 755–762. https://doi.org/10.1016/j.chb.2010.10.023

Chen, J. (2022). Dummy coding. In *The SAGE Encyclopaedia of Research Design* (pp. 464–467). SAGE Publications, Inc. https://doi.org/10.4135/9781071812082.n173

Chen, Y., Li, M., Guo, F., & Wang, X. (2022). The effect of short-form video addiction on users' attention. *Behaviour & Information Technology*, *42*(16), 1–18. https://doi.org/10.1080/0144929x.2022.2151512

Cho, J. (2015). Roles of Smartphone App Use in Improving Social Capital and Reducing Social Isolation. *Cyberpsychology, Behavior, and Social Networking*, *18*(6), 350–355. https://doi.org/10.1089/cyber.2014.0657

Cho, S. E. (2010). *A cross-cultural comparison of Korean and American social network sites: Exploring cultural differences in social relationships and self-presentation* [PhD Dissertation]. https://eric.ed.gov/?id=ED514122

Choi, T. R., Sung, Y., Lee, J.-A., & Choi, S. M. (2017). Get behind my selfies: The Big Five traits and social networking behaviors through selfies. *Personality and Individual Differences*, *109*, 98–101. https://doi.org/10.1016/j.paid.2016.12.057

Christakis, D. A. (2019). The challenges of defining and studying "digital addiction" in children. *JAMA*, *321*(23), 2277–2278. https://doi.org/10.1001/jama.2019.4690

Chugh, S., Bansal, Y., Nagpal, R., Sakshi, S., Kaur, S. P., Saluja, S., Ahluwalia, B., & Sharma, S. (2024). The Impact of Social Media on Mental Health: Voices From College Students. In *Ethical Marketing Through Data Governance Standards and Effective Technology* (pp. 271–284). IGI Global Scientific Publishing. https://doi.org/10.4018/979-8-3693-2215-4.ch022

Chyung, S. Y., Roberts, K., Swanson, I., & Hankinson, A. (2017). Evidence-Based survey design: The use of a midpoint on the likert scale. *Performance Improvement*, *56*(10), 15–23.

Çî̧çek, I., Şanlı, M. E., Arslan, G., & Yıldırım, M. (2024). Problematic social media use, satisfaction with life, and levels of depressive symptoms in university students during the COVID-19 pandemic: Mediation role of social support. *Psihologija*, *57*(2), 177–197. https://doi.org/10.2298/psi220613009c

Clayton, R. B., Leshner, G., & Almond, A. (2015). The extended iSelf: The impact of iPhone separation on cognition, emotion, and physiology. *Journal of Computer-Mediated Communication*, *20*(2), 119–135. https://doi.org/10.1111/jcc4.12109

Clement, J. (2024, February 5). *Global active streamers on Twitch 2020*. Statista. https://www.statista.com/statistics/746173/monthly-active-streamers-on-twitch/

Cleofas, J. V., Albao, B. T., & Dayrit, J. C. S. (2022). Emerging Adulthood Uses and Gratifications of Social Media During the COVID-19 Pandemic: A Mixed Methods Study Among Filipino College Students. *Emerging Adulthood*, *10*(6), 216769682211286. https://doi.org/10.1177/21676968221128621

Cohen, J. (2013). *Statistical Power Analysis for the Behavioral Sciences* (2nd ed.). Routledge. https://doi.org/10.4324/9780203771587

Coleman, J. S. (1988). Social capital in the creation of human capital. *American Journal of Sociology*, *94*, S95–S120. https://www.jstor.org/stable/2780243

Coleman, J. S. (1990). Commentary: Social Institutions and Social Theory. *American Sociological Review*, *55*(3), 333. https://doi.org/10.2307/2095759

Çömlekçi, M. F., & Başol, O. (2019). Analysis of relationship between youths' social media usage motives and social media addiction. *Celal Bayar University Journal of Social Sciences*, *17*(4), 173–188. https://doi.org/10.18026/cbayarsos.525652

Cook, R. D. (1977). Detection of influential observation in linear regression. *Technometrics*, *19*(1), 15–18. https://doi.org/10.1080/00401706.1977.10489493

Cook, R. D., & Weisberg, S. (1982). Criticism and influence analysis in regression. *Sociological Methodology*, *13*, 313. https://doi.org/10.2307/270724

Coolican, H. (2024). *Research methods and statistics in psychology* (8th ed.). Routledge.

Correa, T., Hinsley, A. W., & de Zúñiga, H. G. (2010). Who interacts on the Web?: The intersection of users' personality and social media use. *Computers in Human Behavior*, *26*(2), 247–253. https://doi.org/10.1016/j.chb.2009.09.003

Cotten, S. R., Ghaiumy Anaraky, R., & Schuster, A. M. (2023). Social media use may not be as bad as some suggest: Implication for older adults. *Innovation in Aging*, *7*, 1–9. https://doi.org/10.1093/geroni/igad022

Coyne, P., Voth, J., & Woodruff, S. J. (2023). A comparison of self-report and objective measurements of smartphone and social media usage. *Telematics and Informatics Reports*, *10*, 100061. https://doi.org/10.1016/j.teler.2023.100061

Cramer, D. (2003). Chapter 6: Hierarchical multiple regression. In *Advanced Quantitative Data Analysis* (pp. 74–85). Open University Press.

Crowston, K., & Fagnot, I. (2018). Stages of motivation for contributing user-generated content: A theory and empirical test. *International Journal of Human-Computer Studies*, *109*, 89–101. https://doi.org/10.1016/j.ijhcs.2017.08.005

Cui, Z. (2021). Analysis of the impact of social media on the economy. *Proceedings of the 2021 3rd International Conference on Economic Management and Cultural Industry (ICEMCI 2021)*, 3062–3066. https://doi.org/10.2991/assehr.k.211209.500

Custer, C. (2016, June 3). *Why China's biggest app has sputtered everywhere else*. Fast Company. https://www.fastcompany.com/3060494/why-chinas-biggest-social-app-has-sputtered-overseas

Cuthbertson, A. (2025, March 31). *US TikTok ban: How it became the world's most controversial app*. The Independent. https://www.independent.co.uk/tech/tiktok-banned-trump-map-countries-downloads-b2682322.html

D'Agata, M. T., & Kwantes, P. J. (2020). Personality Factors Predicting Disinhibited and Risky Online Behaviors. *Journal of Individual Differences*, *41*(4), 1–8. https://doi.org/10.1027/1614-0001/a000321

Da-yong, Z., & Zhan, S. (2022). Short video users' personality traits and social sharing motivation. *Frontiers in Psychology*, *13*. https://doi.org/10.3389/fpsyg.2022.1046735

Daei, A., Ashrafi-rizi, H., & Soleymani, M. R. (2019). Nomophobia and health hazards: Smartphone use and addiction among university students. *International Journal of Preventive Medicine*, *10*(1), 202. https://doi.org/10.4103/ijpvm.ijpvm 184 19

Dahl, D., & Bergmark, K. H. (2020). Persistence in problematic internet use—A systematic review and meta-analysis. *Frontiers in Sociology*, *5*. https://doi.org/10.3389/fsoc.2020.00030

Dahlgren, C., & Enshagen, L. (2023). *To whom do we listen, and why?: An exploratory study into how young adult consumers experience TikTok electronic word-of-mouth product recommendations* [Master Thesis]. https://hj.diva-portal.org/smash/record.jsf?pid=diva2%3A1762494&dswid=-6795

Dalley, J. W., Everitt, B. J., & Robbins, T. W. (2011). Impulsivity, compulsivity, and top-down cognitive control. *Neuron*, *69*(4), 680–694. https://doi.org/10.1016/j.neuron.2011.01.020

Daugherty, T., Eastin, M. S., & Bright, L. (2008). Exploring consumer motivations for creating User-Generated Content. *Journal of Interactive Advertising*, *8*(2), 16–25. https://doi.org/10.1080/15252019.2008.10722139

Dauk, N. (2021, October 24). Is internet addiction a growing problem? *BBC News*. https://www.bbc.co.uk/news/business-58979895

Davahli, M. R., Karwowski, W., Sonmez, S., & Apostolopoulos, Y. (2020). The hospitality industry in the face of the COVID-19 pandemic: Current topics and research methods. *International Journal of Environmental Research and Public Health*, *17*(20), 1–20. https://doi.org/10.3390/ijerph17207366

Davies, H. (2023, August 3). *What is WeChat? All about the messaging app*. Trusted Reviews. https://www.trustedreviews.com/explainer/what-is-wechat-4355493

De Los Santos, M., & Klug, D. (2021). The TikTok Tradeoff: Compelling Algorithmic Content at the Expense of Personal Privacy. *Proceedings of the 20th International Conference on Mobile and Ubiquitous Multimedia*, 226–229. https://doi.org/10.1145/3490632.3497864

Dean, B. (2023, January 5). *TikTok User Statistics (2022)*. Backlinko. https://backlinko.com/tiktok-users

Deci, E. L., & Ryan, R. M. (1985). Intrinsic motivation and self-determination in human behavior. *Contemporary Sociology*, *17*(2).

Deci, E. L., & Ryan, R. M. (2000). The "what" and "why" of goal pursuits: Human needs and the self-determination of behavior. *Psychological Inquiry*, *11*(4), 227–268. https://doi.org/10.1207/S15327965PLI1104 01

Deng, T., Lizardo, V.-B., & Mensa, M. (2023). Cross-Cultural comparison of TikTok uses and gratifications. *Behaviour & Information Technology*, 1–13. https://doi.org/10.1080/0144929x.2023.2270534

Dezuanni, M., Reddan, B., Rutherford, L., & Schoonens, A. (2022). Selfies and Shelfies on #bookstagram and #booktok – Social Media and the Mediation of Australian Teen Reading. *Learning, Media and Technology*, *47*(3), 1–18. https://doi.org/10.1080/17439884.2022.2068575

Dhir, A., Pallesen, S., Torsheim, T., & Andreassen, C. S. (2016). Do age and gender differences exist in selfie-related behaviours? *Computers in Human Behavior*, *63*, 549–555. https://doi.org/10.1016/j.chb.2016.05.053

Dias, P., & Duarte, A. (2022). TikTok practices among teenagers in Portugal: A Uses & Gratifications approach. *Journalism and Media*, *3*(4), 615–632. https://doi.org/10.3390/journalmedia3040041

Diener, E., & Lucas, R. E. (2024). Personality traits. In *Noba textbook series: Psychology*. DEF Publishers. http://noba.to/96u8ecgw

Dimock, M. (2019, January 17). *Defining generations: Where Millennials end and Generation Z begins*. Pew Research Center. https://www.pewresearch.org/short-reads/2019/01/17/where-millennials-end-and-generation-z-begins/

Dixon, S. J. (2024a, January 30). *U.S. number of social media users 2023*. Statista. https://www.statista.com/statistics/278409/number-of-social-network-users-in-the-united-states/

Dixon, S. J. (2024b, February 2). *Most popular social networks worldwide as of January 2024, ranked by number of monthly active users*. Statista. https://www.statista.com/statistics/272014/global-social-networks-ranked-by-number-of-users/

Dixon, S. J. (2024c, August 27). *Most popular global mobile messenger apps as of April 2024, based on number of monthly active users*. Statista. https://www.statista.com/statistics/258749/most-popular-global-mobile-messenger-apps/

Dolan, R., Conduit, J., Fahy, J., & Goodman, S. (2016). Social media engagement behaviour: A uses and gratifications perspective. *Journal of Strategic Marketing*, *24*(3-4), 261–277. https://doi.org/10.1080/0965254X.2015.1095222

Dong, Z., & Xie, T. (2022). Why people love short-form videos? The motivations for using TikTok and implications for well-being. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4089602

Dong, Z., & Xie, T. (2023). How to know who you are through your short video selfies?—Capturing personality via short video selfies. *Frontiers in Psychology*, *14*. https://doi.org/10.3389/fpsyg.2023.1072344

Dotan, A., & Zaphiris, P. (2010). A cross-cultural analysis of Flickr users from Peru, Israel, Iran, Taiwan and the UK. *International Journal of Web Based Communities*, *6*(3), 284. https://doi.org/10.1504/ijwbc.2010.033753

Du, J., Kerkhof, P., & van Koningsbruggen, G. M. (2019). Predictors of social media self-control failure: Immediate gratifications, habitual checking, ubiquity, and notifications. *Cyberpsychology, Behavior, and Social Networking*, *22*(7), 477–485. https://doi.org/10.1089/cyber.2018.0730

Ebrahim, F. (2023). *The dark side of social media: Why is social media so addictive?* [Master's Thesis]. https://jyx.jyu.fi/handle/123456789/86827

Eddy, K. (2024, December 20). *8 facts about Americans and TikTok*. Pew Research Center. https://www.pewresearch.org/short-reads/2024/12/20/8-facts-about-americans-and-tiktok/

Edmondson, H. A. (1980). Pathology of alcoholism. *American Journal of Clinical Pathology*, *74*(5), 725–742.

Eevee & Yoshi [@eeveeandyoshi]. (2023, January 26). *Conversations with Eevee ✨ #meows #catmom #cats #ragdollcat #meowing #catconvos #adorable #catvideos #cattok #cattok #catsoftiktok #eeveeandyoshi #vocalcat #talkativecat #petsoftiktok* [Video]. TikTok. https://www.tiktok.com/@eeveeandyoshi/video/7193025561881496874

Eid, A. (2022). *Problematic, absentminded social media scrolling, and mental health* [Master's Thesis]. https://www.diva-portal.org/smash/record.jsf?pid=diva2%3A1676381&dswid=-9797

✮ella lucille✮ [@ellagoodbooks]. (2023, August, 24) *HI ITS BEEN A WHILE BUT IVE BEEN SO BUSY AND I HIT 20K TY LOVE YOU #booktok #augusttbr #goodreads* [Video]. TikTok. https://www.tiktok.com/@ellagoodbooks/video/7270658065752395051

Ellis, D. A. (2023). Social Media: An Everyday Reality. In *Social Media and Mental Health* (pp. 23–32). Cambridge University Press.

Ellis, D. A., Davidson, B. I., Shaw, H., & Geyer, K. (2019). Do smartphone usage scales predict behavior? *International Journal of Human-Computer Studies*, *130*(130), 86–92. https://doi.org/10.1016/j.ijhcs.2019.05.004

Ellison, N. B., Steinfield, C., & Lampe, C. (2007). The benefits of Facebook "friends": Social capital and college students' use of online social network sites. *Journal of Computer-Mediated Communication*, *12*(4), 1143–1168. https://doi.org/10.1111/j.1083-6101.2007.00367.x

Erikson, E. H. (1950). *Childhood and society*. W W Norton & Co.

Erikson, E. H. (1959). *Identity and the life cycle*. Norton.

Ernala, S. K., Burke, M., Leavitt, A., & Ellison, N. B. (2020). How well do people report time spent on Facebook?: An evaluation of established survey questions with recommendations. *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, 1–14.

Evitts, J. (2022, September 4). TikTok-addicted students delete app during exams. *BBC News*. https://www.bbc.co.uk/news/uk-wales-62720657

Falgoust, G., Winterlind, E., Moon, P., Parker, A., Zinzow, H., & Madathil, K. C. (2022). Applying the uses and gratifications theory to identify motivational factors behind young adult's participation in viral social media challenges on TikTok. *Human Factors in Healthcare*, *2*, 100014. https://doi.org/10.1016/j.hfh.2022.100014

Faucher, K. X. (2018). *Social Capital Online: Alienation and Accumulation* (pp. 6–9). University Of Westminster Press.

Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, *39*(2), 175–191. https://doi.org/10.3758/bf03193146

Fauth-Bühler, M., Mann, K., & Potenza, M. N. (2016). Pathological gambling: A review of the neurobiological evidence relevant for its classification as an addictive disorder. *Addiction Biology*, *22*(4), 885–897. https://doi.org/10.1111/adb.12378

Feldkamp, J. (2021). The Rise of TikTok: The Evolution of a Social Media Platform During COVID-19. In *Digital Responses to Covid-19* (pp. 73–85). Springer.

Felisoni, D. D., & Godoi, A. S. (2018). Cell phone usage and academic performance: An experiment. *Computers & Education*, *117*(117), 175–187. https://doi.org/10.1016/j.compedu.2017.10.006

Ferrari, J. R., & Tibbett, T. P. (2020). Procrastination. In *Encyclopaedia of Personality and Individual Differences* (pp. 4046–4053). Springer.

Festinger, L. (1954). A theory of social comparison processes. *Human Relations*, *7*(2), 117–140. https://doi.org/10.1177/001872675400700202

Field, A. (2024). *Discovering Statistics Using IBM SPSS Statistics* (6th ed.). Sage Publications.

Flake, J. K., & Fried, E. I. (2020). Measurement schmeasurement: Questionable measurement practices and how to avoid them. *Advances in Methods and Practices in Psychological Science*, *3*(4), 456–465. https://doi.org/10.1177/2515245920952393

Flood, A. (2021, June 25). *The rise of BookTok: meet the teen influencers pushing books up the charts*. The Guardian. https://www.theguardian.com/books/2021/jun/25/the-rise-of-booktok-meet-the-teen-influencers-pushing-books-up-the-charts

Fontes-Perryman, E., & Spina, R. (2021). Fear of missing out and compulsive social media use as mediators between OCD symptoms and social media fatigue. *Psychology of Popular Media*, *11*(2). https://psycnet.apa.org/doi/10.1037/ppm0000356

Francisco, M. E. Z., & Ruhela, S. (2021, January 19). Investigating TikTok as an AI user platform. *2021 2nd International Conference on Computation, Automation and Knowledge Management (ICCAKM)*. https://doi.org/10.1109/iccakm50778.2021.9357752

Fricker, R. D., & Schonlau, M. (2002). Advantages and disadvantages of internet research surveys: Evidence from the literature. *Field Methods*, *14*(4), 347–367. https://doi.org/10.1177/152582202237725

Fu, S., Li, H., Liu, Y., Pirkkalainen, H., & Salo, M. (2020). Social media overload, exhaustion, and use discontinuance: Examining the effects of information overload, system feature overload, and social overload. *Information Processing & Management*, *57*(6), 102307. https://doi.org/10.1016/j.ipm.2020.102307

Fukuyama, F. (1999). *The Great Disruption: Human Nature and the Reconstruction of Social Order*. Free Press.

Furnham, A., & Boo, H. C. (2011). A literature review of the anchoring effect. *The Journal of Socio-Economics*, *40*(1), 35–42. https://doi.org/10.1016/j.socec.2010.10.008

Gallander Wintre, M., North, C., & Sugar, L. A. (2001). Psychologists' response to criticisms about research based on undergraduate participants: A developmental perspective. *Canadian Psychology/Psychologie Canadienne*, *42*(3), 216–225. https://doi.org/10.1037/h0086893

Geng, Y., Gu, J., Wang, J., & Zhang, R. (2021). Smartphone addiction and depression, anxiety: The role of bedtime procrastination and self-control. *Journal of Affective Disorders*, *293*, 415–421. https://doi.org/10.1016/j.jad.2021.06.062

Gerson, J., Plagnol, A. C., & Corr, P. J. (2017). Passive and Active Facebook Use Measure (PAUM): Validation and relationship to the Reinforcement Sensitivity Theory. *Personality and Individual Differences*, *117*, 81–90. https://doi.org/10.1016/j.paid.2017.05.034

Giancola, D., Travers, R., & Coulombe, S. (2023). Scrolling Through the COVID-19 Pandemic: Exploring the Perceived Effects of Increased Social Media Use on the Mental Health of Undergraduate University Students. *Social Media + Society*, *9*(2). https://doi.org/10.1177/20563051231177970

Gibbons, F. X., & Gerrard, M. (1989). Effects of upward and downward social comparison on mood states. *Journal of Social and Clinical Psychology*, *8*(1), 14–31. https://doi.org/10.1521/jscp.1989.8.1.14

Giles, D. C. (2002). Chapter 7: Structural equation modelling. In *Advanced Research Methods in Psychology* (pp. 81–98). Taylor & Francis Group.

Gnambs, T., & Kaspar, K. (2016). Socially desirable responding in web-based questionnaires: A meta-analytic review of the Candor hypothesis. *Assessment*, *24*(6), 746–762. https://doi.org/10.1177/1073191115624547

Goldberg, L. R. (1990). An alternative "description of personality": The Big-Five factor structure. *Journal of Personality and Social Psychology*, *59*(6), 1216–1229. https://doi.org/10.1037/0022-3514.59.6.1216

Goldberg, L. R. (1993). The structure of phenotypic personality traits. *American Psychologist*, *48*(1), 26–34. https://doi.org/10.1037/0003-066x.48.1.26

Gosling, S. D., Augustine, A. A., Vazire, S., Holtzman, N., & Gaddis, S. (2011). Manifestations of Personality in Online Social Networks: Self-Reported Facebook-Related Behaviors and Observable Profile Information. *Cyberpsychology, Behavior, and Social Networking*, *14*(9), 483–488. https://doi.org/10.1089/cyber.2010.0087

Gottfried, J. (2024, January 31). *Americans' Social Media Use*. Pew Research Center: Internet, Science & Tech. https://www.pewresearch.org/internet/2024/01/31/americans-social-media-use/

Graziano, W. G., & Eisenberg, N. (1997). Agreeableness: A Dimension of Personality. In *Handbook of Personality Psychology* (pp. 795–824). Academic Press.

Green, D., Polk, X., Arnold, J., Chester, C., & Matthews, J. (2022). The Rise Of TikTok: A Case Study Of The New Social Media Giant. *Management and Economics Research Journal*, *1*(1), 1–6. https://doi.org/10.18639/MERJ.2022.9900063

Greenwood, B. N. (2019). The role of dopamine in overcoming aversion with exercise. *Brain Research*, *1713*, 102–108. https://doi.org/10.1016/j.brainres.2018.08.030

Griffioen, N., van Rooij, M., Lichtwarck-Aschoff, A., & Granic, I. (2020). Toward improved methods in social media research. *Technology, Mind, and Behavior*, *1*(1). https://doi.org/10.1037/tmb0000005

Griffiths, L. E. (2023). Dancing through Social Distance: connectivity and creativity in the online space. *Body, Space & Technology*, *22*(1), 65–81. https://doi.org/10.16995/bst.9700

Grossmann, I., & Santos, H. C. (2020). Individualistic cultures. In *Encyclopedia of Personality and Individual Differences* (pp. 2238–2241). Springer International Publishing. https://doi.org/10.1007/978-3-319-24612-3 2024

Gu, L., Gao, X., & Li, Y. (2022). What drives me to use TikTok: A latent profile analysis of users' motives. *Frontiers in Psychology*, *13*. https://doi.org/10.3389/fpsyg.2022.992824

Gudykunst, W. B., & Nishida, T. (1986). Attributional confidence in low- and high-context cultures. *Human Communication Research*, *12*(4), 525–549. https://doi.org/10.1111/j.1468-2958.1986.tb00090.x

Guftométros, M., & Guerreiro, J. (2021). The effects of cultural differences on social media behaviour. *International Journal of Internet Marketing and Advertising*, *15*(4), 412. https://doi.org/10.1504/ijima.2021.10040885

Günlü, A., Oral, T., Yoo, S., & Chung, S. (2023). Reliability and validity of the problematic TikTok Use Scale among the general population. *Frontiers in Psychiatry*, *14*. https://doi.org/10.3389/fpsyt.2023.1068431

Gustafsson, E., Johnson, P. W., & Hagberg, M. (2010). Thumb postures and physical loads during mobile phone use – A comparison of young adults with and without musculoskeletal symptoms. *Journal of Electromyography and Kinesiology*, *20*(1), 127–135. https://doi.org/10.1016/j.jelekin.2008.11.010

Guyer, J. J., & Vaughan-Johnston, T. I. (2018). Upward and downward social comparisons: A brief historical overview. In *Encyclopedia of Personality and Individual Differences*. Springer. https://doi.org/10.1007/978-3-319-24612-3 1912

Håkansson, P., & Witmer, H. (2015). Social Media and Trust — A Systematic Literature Review. *Journal of Business and Economics*, *6*(3), 517–524. https://doi.org/10.15341/jbe(2155-7950)/03.06.2015/010

halfbakedharvest [@halfbakedharvest]. (2023, January 23). *The best chicken recipe. #baked #crunchy #hothoney #chicken #foodtok #halfbakedharvest #easyrecipes* [Video]. TikTok. https://www.tiktok.com/@halfbakedharvest/video/7191892232016858411

Harris, E. A. (2021, March 20). How Crying on TikTok Sells Books. *The New York Times*. https://www.nytimes.com/2021/03/20/books/booktok-tiktok-video.html

Hasim, H., & Sherlina, L. (2022). TikTok social media as a means of small and medium business promotion. *Journal of World Science*, *1*(1), 1–14. https://doi.org/10.58344/jws.v1i1.1

Hayes, C., Stott, K., Lamb, K. J., & Hurst, G. A. (2020). "Making Every Second Count": Utilizing TikTok and Systems Thinking to Facilitate Scientific Public Engagement and Contextualization of Chemistry at Home. *Journal of Chemical Education*, *97*(10). https://doi.org/10.1021/acs.jchemed.0c00511

Hellemans, J., Willems, K., & Brengman, M. (2021). The New Adult on the Block: Daily Active Users of TikTok Compared to Facebook, Twitter, and Instagram During the COVID-19 Crisis in Belgium. *Advances in Digital Marketing and ECommerce*, 95–103. https://doi.org/10.1007/978-3-030-76520-0 10

Hen, M., & Goroshit, M. (2018). The effects of decisional and academic procrastination on students' feelings toward academic procrastination. *Current Psychology*, *39*(2). https://doi.org/10.1007/s12144-017-9777-3

Herman, L. (2023, October 9). For who page? TikTok creators' algorithmic dependencies. *IASDR 2023: Life-Changing Design*. https://doi.org/10.21606/iasdr.2023.576

Hing, N., Holdsworth, L., Tiyce, M., & Breen, H. (2013). Stigma and problem gambling: Current knowledge and future research directions. *International Gambling Studies*, *14*(1), 64–81. https://doi.org/10.1080/14459795.2013.841722

Hitlin, P., Rainie, L., & Olmstead, K. (2019). *Facebook algorithms and personal data*. https://www.pewresearch.org/internet/2019/01/16/facebook-algorithms-and-personal-data/

Hofstede, G. (1991). *Cultures and organizations: Software of the mind*. McGraw-Hill.

Hofstede, G. (2001). Culture's Consequences: Comparing Values, Behaviors, Institutions, and Organizations across Nations. *Administrative Science Quarterly*, *48*(1), 127.

Hryniszak, G. (2019). Digital Dependency Interrupted: Profiles of Withdrawal for Self-Described Internet Addicts. In *Interfacing Ourselves (1st ed.)*. Routledge.

Huang, C. (2019). Social network site use and Big Five personality traits: A meta-analysis. *Computers in Human Behavior*, *97*. https://doi.org/10.1016/j.chb.2019.03.009

Huang, Y.-T., & Su, S.-F. (2018). Motives for Instagram Use and Topics of Interest among Young Adults. *Future Internet*, *10*(8), 77. https://doi.org/10.3390/fi10080077

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. https://doi.org/10.1016/j.chb.2011.11.001

Husain, W., Haddad, A. J., Husain, M. A., Ghazzawi, H., Trabelsi, K., Ammar, A., Saif, Z., Pakpour, A., & Jahrami, H. (2025). Reliability generalization meta-analysis of the internal consistency of the Big Five Inventory (BFI) by comparing BFI (44 items) and BFI-2 (60 items) versions controlling for age, sex, language factors. *BMC Psychology*, *13*(1). https://doi.org/10.1186/s40359-024-02271-x

Ijaz, D., Araja, J., Walker, S., & Mahmoud, M. (2022). Understanding Context Collapse for Social Media Users. *2022 International Conference on Computational Science and Computational Intelligence (CSCI)*, 807–812. https://doi.org/10.1109/CSCI58124.2022.00147

Intelligent. (2024, April 3). *One-Third of College Students Say TikTok Ban Will Negatively Impact Their Grades*. Intelligent. https://www.intelligent.com/one-third-of-college-students-say-tiktok-ban-will-negatively-impact-their-grades/

Iodice, R., & Papapicco, C. (2021). To be a TikToker in COVID-19 Era: An Experience of Social Influence. *Online Journal of Communication and Media Technologies*, *11*(1), e202103. https://doi.org/10.30935/ojcmt/9615

Jain, A., & Hussenet, A. (2022). Profitability and Polarization: TikTok's Dominance of the Attention Economy. *Journal of Student Research*, *11*(3). https://doi.org/10.47611/jsrhs.v11i3.2963

Jarrar, L. (2023). Older Adults' Usage of Social Media Platforms; Facebook, WhatsApp, Twitter, And TikTok. *Information Sciences Letters*, *12*(9). https://digitalcommons.aaru.edu.jo/isl/vol12/iss9/25

JASP Team. (2021). *JASP (Version 0.14) [Computer software]*. https://jasp-stats.org/

Jerasa, S., & Boffone, T. (2021). BookTok 101: TikTok, Digital Literacies, and Out-of-School Reading Practices. *Journal of Adolescent & Adult Literacy*, *65*(3), 219–226. https://doi.org/10.1002/jaal.1199

Jha, A. K. (2020). Understanding Generation Alpha. *OSF Preprints*. https://doi.org/10.31219/osf.io/d2e8g

Johannes, N., Nguyen, T., Weinstein, N., & Przybylski, A. K. (2021). Objective, subjective, and accurate reporting of social media use: No evidence that daily social media use correlates with personality traits, motivational states, or well-being. *Technology, Mind, and Behavior*, *2*(2). https://doi.org/10.1037/tmb0000035

John, O. P., & Srivastava, S. (1999). The Big-Five trait taxonomy: History, measurement, and theoretical perspectives. In *Handbook of personality: Theory and research (Vol. 2)* (pp. 102–138). Guildford Press.

Johns, R. (2005). One size doesn't fit all: Selecting response scales for attitude items. *Journal of Elections, Public Opinion & Parties*, *15*(2), 237–264. https://doi.org/10.1080/13689880500178849

Johnson, J. (2023, December 2). *UK: social media usage 2023*. Statista. https://www.statista.com/statistics/507405/uk-active-social-media-and-mobile-social-media-users/

Johnson, N. E., Short, J. C., Chandler, J. A., & Jordan, S. L. (2022). Introducing the contentpreneur: Making the case for research on content creation-based online platforms. *Journal of Business Venturing Insights*, *18*, e00328. https://doi.org/10.1016/j.jbvi.2022.e00328

Johnston, K., Tanner, M., Lalla, N., & Kawalski, D. (2013). Social capital: The benefit of Facebook "friends." *Behaviour & Information Technology*, *32*(1), 24–36. https://doi.org/10.1080/0144929X.2010.550063

Joiner, R., Mizen, E., Pinnell, B., Siddique, L., Bradley, A., & Trevalyen, S. (2023). The effect of different types of TikTok dance challenge videos on young women's body satisfaction. *Computers in Human Behavior*, *147*, 107856. https://doi.org/10.1016/j.chb.2023.107856

Junco, R. (2013). Comparing actual and self-reported measures of Facebook use. *Computers in Human Behavior*, *29*(3), 626–631. https://doi.org/10.1016/j.chb.2012.11.007

Jungselius, B., & Weilenmann, A. (2018). Conceptualizing "use" in social media studies. *Proceedings of the 9th International Conference on Social Media and Society*, 325–329. https://doi.org/10.1145/3217804.3217938

Kandasamy, S., Buhari, A. M., & Janaki, S. (2019). A study on anxiety disorder among college students with internet addiction. *International Journal of Community Medicine and Public Health*, *6*(4), 1695. https://doi.org/10.18203/2394-6040.ijcmph20191407

Kang, H., & Lou, C. (2022). AI agency vs. human agency: Understanding human–AI interactions on TikTok and their implications for user engagement. *Journal of Computer-Mediated Communication*, *27*(5). https://doi.org/10.1093/jcmc/zmac014

Kardefelt-Winther, D., Heeren, A., Schimmenti, A., van Rooij, A., Maurage, P., Carras, M., Edman, J., Blaszczynski, A., Khazaal, Y., & Billieux, J. (2017). How can we conceptualize behavioural addiction without pathologizing common behaviours? *Addiction*, *112*(10), 1709–1715. https://doi.org/10.1111/add.13763

Karhu, M., Suoheimo, M., & Häkkilä, J. (2021, May 12). People's Perspectives on Social Media Use during COVID-19 Pandemic. *20th International Conference on Mobile and Ubiquitous Multimedia*. https://doi.org/10.1145/3490632.3490666

Katz, E., Blumler, J. G., & Gurevitch, M. (1973). Uses and Gratifications Research. *The Public Opinion Quarterly*, *37*(4), 509–523. https://www.jstor.org/stable/2747854

Kay, R., Benzimra, D., & Li, J. (2017). Exploring factors that influence technology-based distractions in bring your own device classrooms. *Journal of Educational Computing Research*, *55*(7), 974–995. https://doi.org/10.1177/0735633117690004

Kaye, D. B., Chen, X., & Zeng, J. (2020). The co-evolution of two Chinese mobile short video apps: Parallel platformization of Douyin and TikTok. *Mobile Media & Communication*, *9*(2), 229–253. https://doi.org/10.1177/2050157920952120

Kaye, L. K., Orben, A., A. Ellis, D., C. Hunter, S., & Houghton, S. (2020). The conceptual and methodological mayhem of "screen time." *International Journal of Environmental Research and Public Health*, *17*(10), 3661. https://doi.org/10.3390/ijerph17103661

Kelfve, S., Kivi, M., Johansson, B., & Lindwall, M. (2020). Going web or staying paper? The use of web-surveys among older people. *BMC Medical Research Methodology*, *20*(1). https://doi.org/10.1186/s12874-020-01138-0

Kemp, S. (2025a). *Digital 2025: The United Kingdom* (pp. 91–92). https://datareportal.com/reports/digital-2025-united-kingdom

Kemp, S. (2025b). *Digital 2025: The United States Of America* (pp. 92–93). https://datareportal.com/reports/digital-2025-united-states-of-america

Kendall, T. (2021). From Binge-Watching to Binge-Scrolling. *Film Quarterly*, *75*(1), 41–46. https://doi.org/10.1525/fq.2021.75.1.41

Kim, B., & Kim, Y. (2018). Facebook versus Instagram: How perceived gratifications and technological attributes are related to the change in social media usage. *The Social Science Journal*, *56*(2), 156–167. https://doi.org/10.1016/j.soscij.2018.10.002

Kim, H. Y. (2013). Statistical notes for clinical researchers: Assessing normal distribution (2) using skewness and kurtosis. *Restorative Dentistry & Endodontics*, *38*(1), 52–54. https://doi.org/10.5395%2Frde.2013.38.1.52

Kim, Y., Sohn, D., & Choi, S. M. (2011). Cultural difference in motivations for using social network sites: A comparative study of American and Korean college students. *Computers in Human Behavior*, *27*(1), 365–372. https://doi.org/10.1016/j.chb.2010.08.015

Kıran, S., & Demirçeviren, F. G. (2021). The influence of culture on the motivation for the use of social media: A comparative study of Turkish and German high school students. *Beykoz Akademi Dergisi*, *9*(1), 19–33. https://doi.org/10.14514/byk.m.26515393.2021.9/1.19-33

Kircaburun, K., Alhabash, S., Tosuntaş, Ş. B., & Griffiths, M. D. (2020). Uses and gratifications of problematic social media use among university students: A simultaneous examination of the big five of personality traits, social media platforms, and social media use motives. *International Journal of Mental Health and Addiction*, *18*(18). https://doi.org/10.1007/s11469-018-9940-6

Kircaburun, K., & Griffiths, M. D. (2018). Instagram addiction and the Big Five of personality: The mediating role of self-liking. *Journal of Behavioral Addictions*, *7*(1), 158–170. https://doi.org/10.1556/2006.7.2018.15

Kline, R. B. (2023). *Principles and practice of structural equation modeling* (5th ed.). The Guilford Press.

Klug, D., Qin, Y., Evans, M., & Kaufman, G. (2021). Trick and Please. A Mixed-Method Study On User Assumptions About the TikTok Algorithm. *13th ACM Web Science Conference 2021*, 84–92. https://doi.org/10.1145/3447535.3462512

Kohler, T. J. (2023). *Caught In The Loop: The Effects of The Addictive Nature Of Short-form Videos On Users' Perceived Attention Span And Mood* [Bachelor's Thesis]. https://essay.utwente.nl/96577/

Koob, G. F., & Le Moal, M. (2008). Addiction and the brain antireward system. *Annual Review of Psychology*, *59*(1), 29–53. https://doi.org/10.1146/annurev.psych.59.103006.093548

Krisadhi, R., Kurniyawan, D., Aryawan, D. N., Johan, H. S., & Ishomi, M. I. (2023). Relationship between Gen Z's Personality and Motivations with TikTok Usage During Pandemic. *MediaTor*, *16*(2), 377–397. https://doi.org/10.29313/mediator.v16i2.2665

Krosnick, J. A. (1991). Response strategies for coping with the cognitive demands of attitude measures in surveys. *Applied Cognitive Psychology*, *5*(3), 213–236. https://doi.org/10.1002/acp.2350050305

Kumar, V. L., & Goldstein, M. A. (2020). Cyberbullying and adolescents. *Current Paediatrics Reports*, *8*. https://doi.org/10.1007/s40124-020-00217-6

Kunst, A. (2023a, July 4). *Most well-known social networks in the UK 2023*. Statista. https://www.statista.com/statistics/1309958/most-well-known-social-networks-in-the-uk/

Kunst, A. (2023b, October 16). *Most well-known social networks in the United States 2023*. Statista. https://www.statista.com/statistics/1307244/most-well-known-social-networks-in-the-united-states/

Kurniasanti, K. S., Assandi, P., Ismail, R. I., Nasrun, M. W. S., & Wiguna, T. (2019). Internet addiction: A new addiction? *Medical Journal of Indonesia*, *28*(1), 82–91. https://doi.org/10.13181/mji.v28i1.2752

Kuru, O., & Pasek, J. (2016). Improving social media measurement in surveys: Avoiding acquiescence bias in Facebook research. *Computers in Human Behavior*, *57*, 82–92. https://doi.org/10.1016/j.chb.2015.12.008

Kuss, D. J., & Griffiths, M. D. (2011). Online social networking and addiction--a review of the psychological literature. *International Journal of Environmental Research and Public Health*, *8*(9), 3528–3552. https://doi.org/10.3390/ijerph8093528

Kuss, D., & Griffiths, M. (2017). Social Networking Sites and Addiction: Ten Lessons Learned. *International Journal of Environmental Research and Public Health*, *14*(3), 311. https://doi.org/10.3390/ijerph14030311

Kwak, K. T., Choi, S. K., & Lee, B. G. (2014). SNS flow, SNS self-disclosure and post hoc interpersonal relations change: Focused on Korean Facebook user. *Computers in Human Behavior*, *31*, 294–304. https://doi.org/10.1016/j.chb.2013.10.046

Kwande, A. (2023). *TikTok Under Watch: A Look Into The TikTok Ban and Its Implications on National Security and Free Speech*. https://doi.org/10.57912/23773785.v1

Laajaj, R., Macours, K., Pinzon Hernandez, D. A., Arias, O., Gosling, S. D., Potter, J., Rubio-Codina, M., & Vakis, R. (2019). Challenges to capture the big five personality traits in non-WEIRD populations. *Science Advances*, *5*(7), eaaw5226. https://doi.org/10.1126/sciadv.aaw5226

Lakhan, R., Sharma, B., & Sharma, M. (2023). Chapter 4 - Social media: utility versus addiction. In *Effective Use of Social Media in Public Health* (pp. 65–97). Academic Press. https://doi.org/10.1016/B978-0-323-95630-7.00002-0

Landers, R. N., & Lounsbury, J. W. (2006). An investigation of Big Five and narrow personality traits in relation to Internet usage. *Computers in Human Behavior*, *22*(2), 283–293. https://doi.org/10.1016/j.chb.2004.06.001

Laor, T. (2022). My social network: Group differences in frequency of use, active use, and interactive use on Facebook, Instagram and Twitter. *Technology in Society*, *68*, 101922. https://doi.org/10.1016/j.techsoc.2022.101922

Lapointe, L., Boudreau-Pinsonneault, C., & Vaghefi, I. (2013). Is smartphone usage truly smart? A qualitative investigation of IT addictive behaviors. *46th Hawaii International Conference on System Sciences*. https://doi.org/10.1109/hicss.2013.367

Larssen, L. M. (2023). *Attached to the Algorithm - An explorative study of young adults' user perspective on TikTok* [Master's Thesis]. https://uia.brage.unit.no/uia-xmlui/handle/11250/3083652

Lau, W. W. F. (2017). Effects of social media usage and social media multitasking on the academic performance of university students. *Computers in Human Behavior*, *68*, 286–291. https://doi.org/10.1016/j.chb.2016.11.043

Lee, R. S. C., Hoppenbrouwers, S., & Franken, I. (2019). A systematic meta-review of impulsivity and compulsivity in addictive behaviors. *Neuropsychology Review*, *29*(1), 14–26. https://doi.org/10.1007/s11065-019-09402-x

Lee, Y.-P., Tsai, H., & Wu, J.-S. (2020). Exploring the Impact of User Personality and Self-Disclosure on the Continuous Use of Social Media. *Journal of Economics and Business*, *3*(4). https://doi.org/10.31014/aior.1992.03.04.284

Leentjens, A. F. G., & Levenson, J. L. (2013). Ethical issues concerning the recruitment of university students as research subjects. *Journal of Psychosomatic Research*, *75*(4), 394–398. https://doi.org/10.1016/j.jpsychores.2013.03.007

Lewin, K. M., Ellithorpe, M. E., & Meshi, D. (2022). Social comparison and problematic social media use: Relationships between five different social media platforms and three different social comparison constructs. *Personality and Individual Differences*, *199*, 111865. https://doi.org/10.1016/j.paid.2022.111865

Li, D. X. T. (2023). What should we do about teen social media addiction? A review of social media's impact on development and recommendation for future regulations. *Preprints.org*. https://doi.org/10.20944/preprints202311.1934.v1

Li, H., Fang, Y., Lim, K. H., & Wang, Y. (2019). PlatformBased Function Repertoire, Reputation, and Sales Performance of EMarketplace Sellers. *MIS Quarterly*, *43*(1), 207-A5. JSTOR. https://doi.org/10.2307/26847858

Li, Y., Guan, M., Hammond, P., & Berrey, L. E. (2021). Communicating COVID-19 information on TikTok: a content analysis of TikTok videos from official accounts featured in the COVID-19 information hub. *Health Education Research*, *36*(3). https://doi.org/10.1093/her/cyab010

Li, Y., Liu, Q., & Wang, Y. (2022). The Research on the Usage Behavior of TikTok Short Video Platform in the Elderly Group. *Journal of Education, Humanities and Social Sciences*, *5*, 189–197. https://doi.org/10.54097/ehss.v5i.2901

Li, Y., Sun, Y., Meng, S., Bao, Y., Cheng, J., Chang, X., Ran, M., Sun, Y., Kosten, T., Strang, J., Lu, L., & Shi, J. (2021). Internet addiction increases in the general population during COVID-19: Evidence from China. *The American Journal on Addictions*, *30*(4). https://doi.org/10.1111/ajad.13156

Likert, R. (1932). A technique for the measurement of attitudes. *Archives of Psychology*, *22*(140), 55. https://psycnet.apa.org/record/1933-01885-001

Lin, L. Y., Sidani, J. E., Shensa, A., Radovic, A., Miller, E., Colditz, J. B., Hoffman, B. L., Giles, L. M., & Primack, B. A. (2016). Association between social media use and depression among US young adults. *Depression and Anxiety*, *33*(4), 323–331. https://doi.org/10.1002/da.22466

Lin, Y.-H., Lin, Y.-C., Lee, Y.-H., Lin, P.-H., Lin, S.-H., Chang, L.-R., Tseng, H.-W., Yen, L.-Y., Yang, C. C. H., & Kuo, T. B. J. (2015). Time distortion associated with smartphone addiction: Identifying smartphone addiction via a mobile application (App). *Journal of Psychiatric Research*, *65*, 139–145. https://doi.org/10.1016/j.jpsychires.2015.04.003

Literat, I., & Kligler-Vilenchik, N. (2023). TikTok as a Key Platform for Youth Political Expression: Reflecting on the Opportunities and Stakes Involved. *Social Media + Society*, *9*(1), 205630512311575. https://doi.org/10.1177/20563051231157595

Liu, M., & Wang, Y. (2015). Data collection mode effect on feeling thermometer questions: A comparison of face-to-face and Web surveys. *Computers in Human Behavior*, *48*, 212–218. https://doi.org/10.1016/j.chb.2015.01.057

Longobardi, C., Settanni, M., Fabris, M. A., & Marengo, D. (2020). Follow or be followed: Exploring the links between Instagram popularity, social media addiction, cyber victimization, and subjective happiness in Italian adolescents. *Children and Youth Services Review*, *113*, 104955. https://doi.org/10.1016/j.childyouth.2020.104955

Lu, C., & Wan, C. (2018). Cultural self-awareness as awareness of culture's influence on the self: Implications for cultural identification and well-being. *Personality and Social Psychology Bulletin*, *44*(6), 823–837. https://doi.org/10.1177/0146167217752117

LunaTheMiniCockapoo [@lunatheminicockapoo]. (2023, January 24). *It's the last one for me… 👀 😂 #dogsoftiktok #dogtok #tiktokdogs #dogs #doglife #lunatheminicockapoo* [Video]. TikTok. https://www.tiktok.com/@lunatheminicockapoo/video/7192328834023279877

Lundquist, A. R., Lefebvre, E. J., & Garramone, S. J. (2013). Smartphones: Fulfilling the need for immediacy in everyday life, but at what cost? *International Journal of Humanities and Social Science*, *4*(2), 80–89.

Lyons, A., & Branston, C. (2006). Cross cultural change, adjustment and culture shock: UK to USA. *Tourism: An International Interdisciplinary Journal*, *54*(4), 355–365. https://hrcak.srce.hr/161568

Macit, H. B., Macit, G., & Güngör, O. (2018). A research on social media addiction and dopamine driven feedback. *Mehmet Akif Ersoy Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi*, *5*(3), 882–897. https://doi.org/10.30798/makuiibf.435845

Mackson, S. B., Brochu, P. M., & Schneider, B. A. (2019). Instagram: Friend or foe? The application's association with psychological well-being. *New Media & Society*, *21*(10), 2160–2182. https://doi.org/10.1177/1461444819840021

Madianou, M. (2014). Smartphones as Polymedia. *Journal of Computer-Mediated Communication*, *19*(3), 667–680. https://doi.org/10.1111/jcc4.12069

Mahalingham, T., McEvoy, P. M., & Clarke, P. J. F. (2023). Assessing the validity of self-report social media use: Evidence of No relationship with objective smartphone use. *Computers in Human Behavior*, *140*, 107567. https://doi.org/10.1016/j.chb.2022.107567

Maheshwari, S., & Holpuch, A. (2023, October 10). Why Countries Are Trying to Ban TikTok. *The New York Times*. https://www.nytimes.com/article/tiktok-ban.html

Maiorca, D. (2023, November 13). *In What Countries Is TikTok Banned?* MUO. https://www.makeuseof.com/what-countries-is-tiktok-banned/

Marciano, L., & Camerini, A.-L. (2022). Duration, frequency, and time distortion: Which is the best predictor of problematic smartphone use in adolescents? A trace data study. *PLOS ONE*, *17*(2), e0263815. https://doi.org/10.1371/journal.pone.0263815

Marcus, A., & Krishnamurthi, N. (2009). Cross-Cultural analysis of social network services in Japan, Korea, and the USA. *International Conference on Internationalization, Design and Global Development*, 59–68. https://link.springer.com/chapter/10.1007/978-3-642-02767-3 7

Marek, J. (2023). The impatient gaze: on the phenomenon of scrolling in the age of boredom. *Semiotica*, *2023*(254), 107–135. https://doi.org/10.1515/sem-2023-0125

Marengo, D., Sindermann, C., Elhai, J. D., & Montag, C. (2020). One Social Media Company to Rule Them All: Associations Between Use of Facebook-Owned Social Media Platforms, Sociodemographic Characteristics, and the Big Five Personality Traits. *Frontiers in Psychology*, *11*. https://doi.org/10.3389/fpsyg.2020.00936

Marino, C., Vieno, A., Moss, A. C., Caselli, G., Nikčević, A. V., & Spada, M. M. (2016). Personality, motives and metacognitions as predictors of problematic Facebook Use in university students. *Personality and Individual Differences*, *101*, 70–77. https://doi.org/10.1016/j.paid.2016.05.053

Marshall, T. C., Lefringhausen, K., & Ferenczi, N. (2015). The Big Five, self-esteem, and narcissism as predictors of the topics people write about in Facebook status updates. *Personality and Individual Differences*, *85*(0191-8869), 35–40. https://doi.org/10.1016/j.paid.2015.04.039

Masciantonio, A., & Bourguignon, D. (2023). Motivation Scale for Using Social Network Sites: Comparative Study between Facebook, Instagram, Twitter, Snapchat and LinkedIn. *Psychologica Belgica*, *63*(1), 30–43. https://doi.org/10.5334/pb.1161

Masciantonio, A., Bourguignon, D., Bouchat, P., Balty, M., & Rimé, B. (2021). Don't put all social network sites in one basket: Facebook, Instagram, Twitter, TikTok, and their relations with well-being during the COVID-19 pandemic. *PLOS ONE*, *16*(3), e0248384. https://doi.org/10.1371/journal.pone.0248384

Matsa, K. E. (2023, November 15). *More Americans are getting news on TikTok, bucking the trend seen on most other social media sites*. Pew Research Center. https://www.pewresearch.org/short-reads/2023/11/15/more-americans-are-getting-news-on-tiktok-bucking-the-trend-seen-on-most-other-social-media-sites/

Matsumoto, D., Kudoh, T., & Takeuchi, S. (1996). Changing Patterns of Individualism and Collectivism in the United States and Japan. *Culture & Psychology*, *2*(1), 77–107. https://doi.org/10.1177/1354067x9621005

Matsuzaki, T., Nishimura, K., & Higuchi, S. (2023). Screening for forms of problematic Internet usage. *Current Opinion in Behavioral Sciences*, *50*, 101260–101260. https://doi.org/10.1016/j.cobeha.2023.101260

Matthews, G., Deary, I. J., & Whiteman, M. C. (2009). *Personality Traits*. Cambridge University Press.

McAlaney, J., Almourad, M. B., Powell, G., & Ali, R. (2020). Perceptions and misperceptions of smartphone use: Applying the social norms approach. *Information*, *11*(11), 513. https://doi.org/10.3390/info11110513

McAndrew, F. T., & Jeong, H. S. (2012). Who does what on Facebook? Age, sex, and relationship status as predictors of Facebook use. *Computers in Human Behavior*, *28*(6), 2359–2365. https://doi.org/10.1016/j.chb.2012.07.007

McCarthy, C. (2008, June 20). *ComScore: Facebook is beating MySpace worldwide*. CNET. https://www.cnet.com/culture/comscore-facebook-is-beating-myspace-worldwide/

McCashin, D., & Murphy, C. M. (2022). Using TikTok for public and youth mental health – A systematic review and content analysis. *Clinical Child Psychology and Psychiatry*, *28*(1), 135910452211066. https://doi.org/10.1177/13591045221106608

McClain, C. (2023, July 10). *Majority of Americans say TikTok is a threat to national security*. Pew Research Center. https://www.pewresearch.org/short-reads/2023/07/10/majority-of-americans-say-tiktok-is-a-threat-to-national-security/

McCrae, R. R., & Costa, P. T. (1987). Validation of the five-factor model of personality across instruments and observers. *Journal of Personality and Social Psychology*, *52*(1), 81–90. https://doi.org/10.1037/0022-3514.52.1.81

McCrae, R. R., & John, O. P. (1992). An introduction to the Five-Factor Model and its applications. *Journal of Personality*, *60*(2), 175–215. https://doi.org/10.1111/j.1467-6494.1992.tb00970.x

McGill, T., Klobas, J., & Moghavvemi, S. (2023). Time distortion in student YouTube use: The effects of use motivation, personality, and pattern of use on study efficiency. *Australasian Journal of Educational Technology*, *39*(1), 71–87. https://doi.org/10.14742/ajet.7705

McIntyre, K. E. (2014). The Evolution of Social Media from 1969 to 2013: A Change in Competition and a Trend Toward Complementary, Niche Sites. *The Journal of Social Media in Society*, *3*(2). https://thejsms.org/index.php/JSMS/article/view/89

McLaughlin, C., & Stephens, S. (2019). The theory of planned behavior: the social media intentions of SMEs. *Irish Academy of Management*. https://www.researchgate.net/publication/330412288 The theory of planned behavior the social media intentions of SMEs

McMahon, C. (2019). *The Psychology of Social Media*. Routledge.

Meier, A. (2021). Studying problems, not problematic usage: Do mobile checking habits increase procrastination and decrease well-being? *Mobile Media & Communication*, *10*(2), 205015792110293. https://doi.org/10.1177/20501579211029326

Mekler, A. (2021). The Effects of TikTok Use on College Student Learning. *Undergraduate Review*, *16*(1), 145–153. https://vc.bridgew.edu/undergrad rev/vol16/iss1/19/

Meng, K. S., & Leung, L. (2021). Factors influencing TikTok engagement behaviors in China: An examination of gratifications sought, narcissism, and the Big Five personality traits. *Telecommunications Policy*, *45*(7), 102172. https://doi.org/10.1016/j.telpol.2021.102172

Merga, M. K. (2021). How can Booktok on TikTok inform readers' advisory services for young people? *Library & Information Science Research*, *43*(2), 101091. https://doi.org/10.1016/j.lisr.2021.101091

Meshi, D., Tamir, I., & Heekeren, H. R. (2015). Neural correlates of social media engagement: Implications for addictive behaviors. *Social Cognitive and Affective Neuroscience*, *10*(3), 422–429.

Microsoft Corporation. (2018). *Microsoft Excel*. Retrieved from https://office.microsoft.com/excel

Miller, E. T., Neal, D. J., Roberts, L. J., Baer, J. S., Cressler, S. O., Metrik, J., & Marlatt, G. A. (2002). Test-retest reliability of alcohol measures: Is there a difference between Internet-based assessment and traditional methods? *Psychology of Addictive Behaviors*, *16*(1), 56–63. https://doi.org/10.1037/0893-164x.16.1.56

Moglia, P. (2018). *Salem Health: Addictions & Substance Abuse* (2nd ed., pp. 41–44). Salem Press.

Mohrman, S. A., & Lawler, E. E. (2012). Generating knowledge that drives change. *Academy of Management Perspectives*, *26*(1), 41–51. https://www.jstor.org/stable/23208284

Montag, C., Sindermann, C., & Becker, B. (2017). Smartphone usage and dopamine release: The effects of smartphone addiction on the brain's reward system. *Journal of Behavioral Addictions*, *6*(3), 123–135.

Montag, C., Yang, H., & Elhai, J. D. (2021). On the Psychology of TikTok Use: A First Glimpse From Empirical Findings. *Frontiers in Public Health*, *9*(1). https://doi.org/10.3389/fpubh.2021.641673

Moore, K., & McElroy, J. C. (2012). The influence of personality on Facebook usage, wall postings, and regret. *Computers in Human Behavior*, *28*(1), 267–274. https://doi.org/10.1016/j.chb.2011.09.009

Moran, G., Muzellec, L., & Johnson, D. (2020). Message content features and social media engagement: Evidence from the media industry. *Journal of Product & Brand Management*, *29*(5), 533–545. https://doi.org/10.1108/jpbm-09-2018-2014

Moretta, T., & Wegmann, E. (2025). Toward the classification of social media use disorder: Clinical characterization and proposed diagnostic criteria. *Addictive Behaviors Reports*, *21*, 100603. https://doi.org/10.1016/j.abrep.2025.100603

Muench, C., Link, J., & Carolus, A. (2022). The surprise of underestimation: Analyzing the effects and predictors of the accuracy of estimated smartphone use. *Design, Operation and Evaluation of Mobile Communications*, 171–190.

Munro, M.-M. (2022). All Work and No Play Makes TikTok a Dull Platform: The Influence of TikTok's "Hustle Culture" on Productivity in the Digital Age. *Intersect: The Stanford Journal of Science, Technology, and Society*, *16*(1). https://ojs.stanford.edu/ojs/index.php/intersect/article/view/2309

Musch, J., & Reips, U.-D. (2000). A brief history of web experimenting. In *Psychological Experiments on the Internet* (pp. 61–87). Academic Press.

Naab, T. K., & Sehl, A. (2016). Studies of user-generated content: A systematic review. *Journalism: Theory, Practice & Criticism*, *18*(10), 1256–1273. https://doi.org/10.1177/1464884916673557

Nagel, T. W. S., Remillard, C., Aucoin, R., & Takenishi, A. (2018). Finding on student use of social media at the collegiate, undergraduate, and graduate levels: Implications for post-secondary educators. *Journal of University Teaching and Learning Practice*, *15*(1), 98–114. https://doi.org/10.53761/1.15.1.8

Nagy, E. (2022, March 25). *BookTok: The Revival of Reading*. The Auburn Plainsman. https://www.theplainsman.com/article/2022/03/booktok-the-revival-of-reading

Nair, R. K., Ganatra, V., Sugumaran, H. A., Kee, D. M. H., Heng, S. W., Mei, H., Huang, C., & Doshi, V. (2022). How Does Social Media Platforms Help to Improve Business Performances during the COVID-19 Pandemic? A Study of TikTok. *Journal of the Community Development in Asia*, *5*(1), 41–53. https://doi.org/10.32535/jcda.v5i1.1384

Nasti, L., Michienzi, A., & Guidi, B. (2020). Discovering the impact of notifications on social network addiction. *From Data to Models and Back: 9th International Symposium*, 72–86. https://doi.org/10.1007/978-3-030-70650-0 5

Navlakha, M. (2023, December 1). *Which countries have banned TikTok?* Mashable. https://mashable.com/article/tiktok-ban-countries

Ng, R., & Indran, N. (2022). Not Too Old for TikTok: How Older Adults are Reframing Aging. *The Gerontologist*, *62*(8). https://doi.org/10.1093/geront/gnac055

Ng, R., & Indran, N. (2023). Granfluencers on TikTok: Factors linked to positive self-portrayals of older adults on social media. *PLOS ONE*, *18*(2), e0280281. https://doi.org/10.1371/journal.pone.0280281

Nijssen, S. R. R., Schaap, G., & Verheijen, G. P. (2018). Has your smartphone replaced your brain? Construction and validation of the Extended Mind Questionnaire (XMQ). *PLOS ONE*, *13*(8), e0202188. https://doi.org/10.1371/journal.pone.0202188

Nong, W., He, Z., Ye, J.-H., Wu, Y.-F., Wu, Y.-T., Ye, J.-N., & Sun, Y. (2023). The Relationship between Short Video Flow, Addiction, Serendipity, and Achievement Motivation among Chinese Vocational School Students: The Post-Epidemic Era Context. *Healthcare*, *11*(4), 462. https://doi.org/10.3390/healthcare11040462

O'Day, E. B., & Heimberg, R. G. (2021). Social media use, social anxiety, and loneliness: A systematic review. *Computers in Human Behavior Reports*, *3*(100070). https://doi.org/10.1016/j.chbr.2021.100070

Obar, J. A., & Wildman, S. (2015). Social media definition and the governance challenge: An introduction to the special issue. *Telecommunications Policy*, *39*(9), 745–750. https://doi.org/10.1016/j.telpol.2015.07.014

Ofcom. (2024). Adults' Media Use and Attitudes Report. In *Ofcom*. https://www.ofcom.org.uk/media-use-and-attitudes/media-habits-adults/adults-media-use-and-attitudes

Omar, B., & Dequan, W. (2020). Watch, share or create: The influence of personality traits and user motivation on TikTok mobile video usage. *International Journal of Interactive Mobile Technologies (IJIM)*, *14*(04), 121–137. https://doi.org/10.3991/ijim.v14i04.12429

Orchard, L. J. (2019). Uses and Gratifications of Social Media: Who Uses It and Why? In *The Oxford Handbook of Cyberpsychology* (pp. 331–432). Oxford University Press.

Orr, J. M., Sackett, P. R., & Dubois, C. L. Z. (1991). Outlier detection and treatment in I/O psychology: A survey of researcher beliefs and an empirical illustration. *Personnel Psychology*, *44*(3), 473–486. https://doi.org/10.1111/j.1744-6570.1991.tb02401.x

Osborne, J., & Overbay, A. (2004). The power of outliers (and why researchers should ALWAYS check for them). *Practical Assessment, Research, and Evaluation*, *9*(6), 6. https://doi.org/10.7275/qf69-7k43

Ostrovsky, A. M., & Chen, J. R. (2020). TikTok and Its Role in Coronavirus Disease 2019 Information Propagation. *Journal of Adolescent Health*, *67*(5). https://doi.org/10.1016/j.jadohealth.2020.07.039

Oulasvirta, A., Rattenbury, T., Ma, L., & Raita, E. (2011). Habits make smartphone use more pervasive. *Personal and Ubiquitous Computing*, *16*(1), 105–114. https://doi.org/10.1007/s00779-011-0412-2

Ozimek, P., & Bierhoff, H.-W. (2016). Facebook use depending on age: The influence of social comparisons. *Computers in Human Behavior*, *61*, 271–279. https://doi.org/10.1016/j.chb.2016.03.034

Ozimek, P., Brailovskaia, J., & Bierhoff, H.-W. (2023). Active and Passive Behavior in Social Media: Validating the Social Media Activity Questionnaire (SMAQ). *Telematics and Informatics Reports*, *10*, 100048. https://doi.org/10.1016/j.teler.2023.100048

Pagani, M., Hofacker, C. F., & Goldsmith, R. E. (2011). The influence of personality on active and passive use of social networking sites. *Psychology and Marketing*, *28*(5), 441–456. https://doi.org/10.1002/mar.20395

Palmgreen, P. (1984). Uses and Gratifications: A Theoretical Perspective. *Annals of the International Communication Association*, *8*(1), 20–55. https://doi.org/10.1080/23808985.1984.11678570

Pan, W., Mu, Z., Zhao, Z., & Tang, Z. (2023). Female Users' TikTok Use and Body Image: Active Versus Passive Use and Social Comparison Processes. *Cyberpsychology, Behavior, and Social Networking*, *26*(1). https://doi.org/10.1089/cyber.2022.0169

Pangrazio, L., & Selwyn, N. (2018). "It's Not Like It's Life or Death or Whatever": Young People's Understandings of Social Media Data. *Social Media + Society*, *4*(3), 205630511878780. https://doi.org/10.1177/2056305118787808

Papacharissi, Z., & Rubin, A. M. (2000). Predictors of Internet Use. *Journal of Broadcasting & Electronic Media*, *44*(2), 175–196. https://doi.org/10.1207/s15506878jobem4402 2

Pardede, P. (2019). Print vs Digital Reading Comprehension in EFL. *JET (Journal of English Teaching)*, *5*(2), 77. https://doi.org/10.33541/jet.v5i2.1062

Parry, D. A., Davidson, B. I., Sewall, C. J. R., Fisher, J. T., Mieczkowski, H., & Quintana, D. S. (2021). A systematic review and meta-analysis of discrepancies between logged and self-reported digital media use. *Nature Human Behaviour*, *5*(11), 1535–1547. https://doi.org/10.1038/s41562-021-01117-5

Parry, D. A., & Le Roux, D. B. (2021). "Cognitive control in media multitaskers" ten years on: A meta-analysis. *Cyberpsychology: Journal of Psychosocial Research on Cyberspace*, *15*(2). https://doi.org/10.5817/cp2021-2-7

Pasaribu, A. G., & Naibaho, F. R. (2021). Teachers' Perceptions of Using TikTok in Students' interest during the COVID-19 Pandemic. *Turkish Online Journal of Qualitative Inquiry*, *12*(9), 5769–5776.

Pearlstein, D., & Dellamore, J. (2023). Montana is Trying to Ban TikTok. What Does the First Amendment Have to Say? *Online Publications*, *76*. https://larc.cardozo.yu.edu/faculty-online-pubs/76

Peck, D. S. (2008). Hanging Out and Growing up with Social Media. *Media Psychology Review*, *1*(1). https://mprcenter.org/review/peckhanging-out/

Pejić, M., Tenjović, L., & Knežević, G. (2014). Validation of the BFI-10 questionnaire - Short version of the big five inventory. *Primenjena Psihologija*, *7*(1), 45. https://doi.org/10.19090/pp.2014.1.45-92

Pempek, T. A., Yermolayeva, Y. A., & Calvert, S. L. (2009). College students' social networking experiences on Facebook. *Journal of Applied Developmental Psychology*, *30*(3), 227–238. https://doi.org/10.1016/j.appdev.2008.12.010

Peterka-Bonetta, J., Sindermann, C., Elhai, J. D., & Montag, C. (2021). How objectively measured Twitter and Instagram use relate to self-reported personality and tendencies toward Internet/Smartphone Use Disorder. *Human Behavior and Emerging Technologies*, *3*(5). https://doi.org/10.1002/hbe2.243

Petrosyan, A. (2024, January 31). *Global digital population 2023*. Statista. https://www.statista.com/statistics/617136/digital-population-worldwide/

Pew Research Center. (2023, November 15). *Social Media and News Fact Sheet*. Pew Research Center's Journalism Project. https://www.pewresearch.org/journalism/fact-sheet/social-media-and-news-fact-sheet/

Philip, A. V., & Zakkariya, K. A. (2016). Big five personality traits and social media presence: Some research insights. *BScan – a Biannual Research Journal of Management and Socio-Economic Transformation*, *1*(1), 65–72.

Pick, J., Sarkar, A., & Rosales, J. (2019). Social Media Use in American Counties: Geography and Determinants. *ISPRS International Journal of Geo-Information*, *8*(9), 424. https://doi.org/10.3390/ijgi8090424

PItre, J. (2023). TikTok, Creation, and the Algorithm. *The Velvet Light Trap*, *91*(1), 71–74. https://muse.jhu.edu/article/881100

Piwek, L., & Joinson, A. (2016). "What do they snapchat about?" Patterns of use in time-limited instant messaging service. *Computers in Human Behavior*, *54*(4), 358–367. https://doi.org/10.1016/j.chb.2015.08.026

Ponce, A. (2023). *Social Media: Are You Addicted? Examining the Role of Social Media Platforms on Life Satisfaction, Personality and Generation* [Dissertation]. https://scholarlycommons.pacific.edu/uop etds/4199

Prakasha, G. S., Anthony, K., & Lapina, M. (2023). Social media disorder in relation to device screen time and autosuggested social media content engagement. *KONTAKT - Journal of Nursing & Social Sciences Related to Health & Illness*, *25*(2), 117–123.

Priporas, C.-V., Stylos, N., & Fotiadis, A. K. (2017). Generation Z consumers' expectations of interactions in smart retailing: A future agenda. *Computers in Human Behavior*, *77*(1), 374–381. https://doi.org/10.1016/j.chb.2017.01.058

Prolific. (2025). *Prolific · Quickly find research participants you can trust.* Prolific. https://prolific.com/

Przybylski, A. K., & Weinstein, N. (2012). Can You Connect with Me Now? How the Presence of Mobile Communication Technology Influences Face-to-Face Conversation Quality. *Journal of Social and Personal Relationships*, *30*(3), 237–246. https://doi.org/10.1177/0265407512453827

Putri, R. P. (2021). TikTok as an online learning media during a pandemic - Case Study: Dance Creativity Course. *Proceedings of the 6th International Conference on Education & Social Sciences (ICESS 2021)*, 282–287. https://doi.org/10.2991/assehr.k.210918.052

Putro, T., & Palupi, P. (2022). Tiktok and Online Selective Self-Presentation. *Proceedings of the International Conference on Community Empowerment and Engagement (ICCEE 2021)*, 33–42. https://doi.org/10.2991/assehr.k.220501.005

Pychyl, T. A., Lee, J. M., Thibodeau, R., & Blunt, A. (2000). Five days of emotion: An experience sampling study of undergraduate student procrastination. *Journal of Social Behavior & Personality*, *15*(5), 239–254. https://psycnet.apa.org/record/2002-10572-019

Qin, Y., Musetti, A., & Omar, B. (2023). Flow Experience Is a Key Factor in the Likelihood of Adolescents' Problematic TikTok Use: The Moderating Role of Active Parental Mediation. *International Journal of Environmental Research and Public Health*, *20*(3), 2089. https://doi.org/10.3390/ijerph20032089

Qiu, J. (2022). How TikTok Satisfies the Public's Psychological Needs—A Perspective From the Uses and Gratifications Theory. *Proceedings of the 2021 International Conference on Social Development and Media Communication (SDMC 2021)*, 1080–1083. https://doi.org/10.2991/assehr.k.220105.199

Qiu, L., Lu, J., Yang, S., Qu, W., & Zhu, T. (2015). What does your selfie say about you? *Computers in Human Behavior*, *52*, 443–449. https://doi.org/10.1016/j.chb.2015.06.032

Qiu, Y. (2024). Social comparison on social media platforms: A media and communication perspective. *International Conference on Language and Cultural Communication (ICLCC)*, *185*. https://doi.org/10.1051/shsconf/202418503008

Qualtrics. (2023). *Qualtrics [Computer software].* https://www.qualtrics.com/

Quan-Haase, A., & Young, A. L. (2010). Uses and Gratifications of Social Media: A Comparison of Facebook and Instant Messaging. *Bulletin of Science, Technology & Society*, *30*(5), 350–361. https://doi.org/10.1177/0270467610380009

Quinn, K. (2018). Cognitive effects of social media use: A case of older adults. *Social Media + Society*, *4*(3), 205630511878720. https://doi.org/10.1177/2056305118787203

Quinn, S. (2019). Positive aspects of social media. In *The Oxford Handbook of Cyberpsychology* (pp. 413–431). Oxford University Press.

Ralph, C. [@charli.ralph]. (2024, March 8). *4 hours of cleaning and a 56 second video 😰 #cleantok #lifestyle #hometok #cleaning* [Video]. TikTok. https://www.tiktok.com/@charli.ralph/video/7343832015495580946

Rammstedt, B., & John, O. P. (2007). Measuring personality in one minute or less: A 10-item short version of the Big Five Inventory in English and German. *Journal of Research in Personality*, *41*(1), 203–212. https://doi.org/10.1016/j.jrp.2006.02.001

Rammstedt, B., Kemper, C. J., & Borg, I. (2012). Correcting Big Five personality measurements for acquiescence: An 18-country cross-cultural study. *European Journal of Personality*, *27*(1), 71–81. https://doi.org/10.1002/per.1894

Rammstedt, B., Lechner, C. M., & Danner, D. (2020). Short Forms Do Not Fall Short. *European Journal of Psychological Assessment*, *37*(1), 1–10. https://doi.org/10.1027/1015-5759/a000574

Ramsden, E., & Talbot, C. V. (2024). The Role of TikTok in Students' Health and Wellbeing. *International Journal of Mental Health and Addiction*. https://doi.org/10.1007/s11469-023-01224-6

Rau, P.-L. P., Peng, S.-Y., & Yang, C.-C. (2006). Time distortion for expert and novice online game players. *CyberPsychology & Behavior*, *9*(4), 396–403. https://doi.org/10.1089/cpb.2006.9.396

Reade, J. (2020). Keeping it raw on the "gram": Authenticity, relatability and digital intimacy in fitness cultures on Instagram. *New Media & Society*, *23*(3), 535–553. https://doi.org/10.1177/1461444819891699

Reis, H. T., Sheldon, K. M., Gable, S. L., Roscoe, J., & Ryan, R. M. (2000). Daily well-being: The role of autonomy, competence, and relatedness. *Personality and Social Psychology Bulletin*, *26*(4), 419–435. https://doi.org/10.1177/0146167200266002

Risko, E. F., & Gilbert, S. J. (2016). Cognitive offloading. *Trends in Cognitive Sciences*, *20*(9), 676–688. https://doi.org/10.1016/j.tics.2016.07.002

Riva, G., & Galimberti, C. (2001). *Towards cyberpsychology: Mind, cognition, and society in the internet age*. IOS Press.

Riva, G., Teruzzi, T., & Anolli, L. (2003). The use of the internet in psychological research: Comparison of online and offline questionnaires. *CyberPsychology & Behavior*, *6*(1), 73–80. https://doi.org/109493103321167983

Roberts, B. W., Jackson, J. J., Fayard, J. V., Edmonds, G., & Meints, J. (2009). Conscientiousness. In *Handbook of individual differences in social behavior* (pp. 369–381). The Guilford Press.

Roberts, J. A., & David, M. E. (2022). On the outside looking in: Social media intensity, social connection, and user well-being: The moderating role of passive social media use. *Canadian Journal of Behavioural Science / Revue Canadienne Des Sciences Du Comportement*, *55*(3). https://doi.org/10.1037/cbs0000323

Roberts, J. A., & David, M. E. (2023). Instagram and TikTok Flow States and Their Association with Psychological Well-Being. *Cyberpsychology, Behavior, and Social Networking*, *26*(2), 80–89. https://doi.org/10.1089/cyber.2022.0117

Roggeveen, A. L., & Sethuraman, R. (2020). How the COVID pandemic may change the world of retailing. *Journal of Retailing*, *96*(2), 169–171. https://doi.org/10.1016/j.jretai.2020.04.002

Rogowska, A. M., & Cincio, A. (2024). Procrastination Mediates the Relationship between Problematic TikTok Use and Depression among Young Adults. *Journal of Clinical Medicine*, *13*(5), 1247. https://doi.org/10.3390/jcm13051247

Romero-Saletti, S. M., Van den Broucke, S., Billieux, J., Karila, L., Kuss, D. J., Rivera Espejo, J. M., Sheldon, P., Lang, C. P., Zimmer-Gembeck, M. J., Zollo, P., Courboin, C., Diez, D., Madison, T. P., Ramos-Diaz, J., Eguia Elias, C. A., & Otiniano, F. (2023). Development, psychometric validation, and cross-cultural comparison of the “Instagram Motives Questionnaire” (IMQ) and the “Instagram Uses and Patterns Questionnaire” (IUPQ). *Journal of Behavioral Addictions*, *12*(1). https://doi.org/10.1556/2006.2022.00088

Romero-Saletti, S. M., Van den Broucke, S., & Van Beggelaer, W. (2022). Understanding Motives, Usage Patterns and Effects of Instagram Use in Youths: A Qualitative Study. *Emerging Adulthood*, *10*(6), 216769682211142. https://doi.org/10.1177/21676968221114251

Ross, C., Orr, E. S., Sisic, M., Arseneault, J. M., Simmering, M. G., & Orr, R. R. (2009). Personality and motivations associated with Facebook use. *Computers in Human Behavior*, *25*(2), 578–586. https://doi.org/10.1016/j.chb.2008.12.024

Roth, R., Ajithkumar, P., Natarajan, G., Achuthan, K., Moon, P., Zinzow, H., & Madathil, K. C. (2022). A Study of Adolescents’ and Young Adults’ TikTok Challenge Participation in South India. *Human Factors in Healthcare*, *1*, 100005. https://doi.org/10.1016/j.hfh.2022.100005

Roy, K., & Swargiary, K. (2024). Exploring advanced media techniques in YouTube content creation: Impacts on viewer engagement and channel sustainability. *[Preprint]*. http://dx.doi.org/10.13140/RG.2.2.19108.28809

Rozgonjuk, D., Kattago, M., & Täht, K. (2018). Social media use in lectures mediates the relationship between procrastination and problematic smartphone use. *Computers in Human Behavior*, *89*, 191–198. https://doi.org/10.1016/j.chb.2018.08.003

Rozgonjuk, D., Levine, J. C., Hall, B. J., & Elhai, J. D. (2018). The association between problematic smartphone use, depression and anxiety symptom severity, and objectively measured smartphone use over one week. *Computers in Human Behavior*, *87*, 10–17. https://doi.org/10.1016/j.chb.2018.05.019

Rubin, A. M. (2009). Uses and gratifications. In *The SAGE Handbook of Media Processes and Effects* (pp. 147–159). Sage.

Rudnichenko, E. (n.d.). *User-Generated Content as the main creative approach on TikTok*. Startups Magazine. https://startupsmagazine.co.uk/article-user-generated-content-main-creative-approach-tiktok

Ruel, E., Wagner, W. E., & Gillespi, B. J. (2016). Pretesting and pilot testing. In *The practice of survey research: Theory and applications* (pp. 101–119). Sage Publications. https://doi.org/10.4135/9781483391700

Rugai, J., & Hamiliton-Ekeke, J. T. (2016). A review of digital addiction: A call for safety education. *Journal of Education and E-Learning Research*, *3*(1), 17–22. https://doi.org/10.20448/journal.509/2016.3.1/509.1.17.22

Ruggiero, T. E. (2000). Uses and gratifications theory in the 21st century. *Mass Communication and Society*, *3*(1), 3–37. https://doi.org/10.1207/s15327825mcs0301 02

Ryan, R. M., & Deci, E. L. (2017). *Self-determination theory: Basic psychological needs in motivation, development, and wellness*. Guilford Press.

Ryan, T., & Xenos, S. (2011). Who uses Facebook? An investigation into the relationship between the Big Five, shyness, narcissism, loneliness, and Facebook usage. *Computers in Human Behavior*, *27*(5), 1658–1664. https://doi.org/10.1016/j.chb.2011.02.004

Ryding, F. C., & Kuss, D. J. (2020). Passive objective measures in the assessment of problematic smartphone use: A systematic review. *Addictive Behaviors Reports*, *11*, 100257. https://doi.org/10.1016/j.abrep.2020.100257

Saini, R., & Chourasiya, A. (2023). The shifting landscape of social media and its implications for the career path of content creators. *International Journal of Advanced Research in Commerce, Management & Social Science*, *6*(1), 1–10. https://www.inspirajournals.com/uploads/Issues/463728405.pdf

Salasac, C., & Lobo, J. T. (2022). The rising popularity of TikTok during the pandemic: Utilization of the application vis-à-vis students' engagement. *American Journal of Interdisciplinary Research and Innovation*, *1*(2), 43–48. https://doi.org/10.54536/ajiri.v1i2.699

Saldaña, M., Mcgregor, S. C., & de Zúñiga, H. G. (2015). Social media as a public space for politics: Cross-national comparison of news consumption and participatory behaviors in the United States and the United Kingdom. *International Journal of Communication*, *9*(1), 3304–3326. https://web.archive.org/web/20180502142136id /http://ijoc.org/index.php/ijoc/article/viewFile/3238/1485

Santos, M. L. B. (2021). The "so-called" UGC: an Updated Definition of user-generated Content in the Age of Social Media. *Online Information Review*, *46*(1), 95–113. https://doi.org/10.1108/oir-06-2020-0258

Scharkow, M. (2016). The accuracy of self-reported internet use—A validation study using client log data. *Communication Methods and Measures*, *10*(1), 13–27. https://doi.org/10.1080/19312458.2015.1118446

Schellewald, A. (2021). On Getting Carried Away By The TikTok Algorithm. *AoIR Selected Papers of Internet Research*, *2021*. https://doi.org/10.5210/spir.v2021i0.12039

Scherr, S., & Wang, K. (2021). Explaining the success of social media with gratification niches: Motivations behind daytime, nighttime, and active use of TikTok in China. *Computers in Human Behavior*, *124*, 106893. https://doi.org/10.1016/j.chb.2021.106893

Scott, C. F., Bay-Cheng, L. Y., Prince, M. A., Nochajski, T. H., & Collins, R. L. (2017). Time spent online: Latent profile analyses of emerging adults' social media use. *Computers in Human Behavior*, *75*, 311–319. https://doi.org/10.1016/j.chb.2017.05.026

Seidman, G. (2013). Self-presentation and belonging on Facebook: How personality influences social media use and motivations. *Personality and Individual Differences*, *54*(3), 402–407. https://doi.org/10.1016/j.paid.2012.10.009

Seitz, L. (2023, May 10). *History of Social Media (It's Younger Than You Think)*. BroadbandSearch. https://www.broadbandsearch.net/blog/complete-history-social-media

Seitz, P. (2015, June 12). *Google's YouTube Gaming challenges Amazon's Twitch*. Investor's Business Daily. https://www.investors.com/news/technology/click/googl-amzn-compete-for-video-game-audience-online/

Sewall, C. J. R., Bear, T. M., Merranko, J., & Rosen, D. (2020). How psychosocial well-being and usage amount predict inaccuracies in retrospective estimates of digital technology use. *Mobile Media & Communication*, *8*(3), 379–399. https://doi.org/10.1177/2050157920902830

Sha, P., & Dong, X. (2021). Research on Adolescents Regarding the Indirect Effect of Depression, Anxiety, and Stress between TikTok Use Disorder and Memory Loss. *International Journal of Environmental Research and Public Health*, *18*(16), 8820. https://doi.org/10.3390/ijerph18168820

Shahnawaz, M. G., & Rehman, U. (2020). Social Networking Addiction Scale. *Cogent Psychology*, *7*(1). https://doi.org/10.1080/23311908.2020.1832032

Shao, G. (2009). Understanding the appeal of user-generated media: A uses and gratification perspective. *Internet Research*, *19*(1), 7–25. https://doi.org/10.1108/10662240910927795

Shao, J., & Lee, S. (2020). The Effect of Chinese Adolescents' Motivation to Use Tiktok on Satisfaction and Continuous Use Intention. *The Journal of the Convergence on Culture Technology*, *6*(2), 107–115. https://doi.org/10.17703/JCCT.2020.6.2.107

Sharabati, A.-A. A., Al-Haddad, S., Al-Khasawneh, M., Nababteh, N., Mohammad, M., & Abu Ghoush, Q. (2022). The Impact of TikTok User Satisfaction on Continuous Intention to Use the Application. *Journal of Open Innovation: Technology, Market, and Complexity*, *8*(3), 125. https://doi.org/10.3390/joitmc8030125

Sheldon, P., & Bryant, K. (2016). Instagram: Motives for its use and relationship to narcissism and contextual age. *Computers in Human Behavior*, *58*, 89–97. https://doi.org/10.1016/j.chb.2015.12.059

Siano, S. J. (2021). *TikTok during an infodemic: How information related to COVID-19 spreads on social media* [Bachelor of Arts Thesis]. http://hdl.handle.net/20.500.12648/11250

Sibona, C., & Choi, J. H. (2021). Factors Affecting End-User Satisfaction on Facebook. *Proceedings of the International AAAI Conference on Web and Social Media*, *6*(1), 575–578. https://doi.org/10.1609/icwsm.v6i1.14284

Sigerson, L., & Cheng, C. (2018). Scales for measuring user engagement with social network sites: A systematic review of psychometric properties. *Computers in Human Behavior*, *83*, 87–105. https://doi.org/10.1016/j.chb.2018.01.023

Silver, M., & Sabini, J. (1981). Procrastinating. *Journal for the Theory of Social Behaviour*, *11*(2), 207–221. https://doi.org/10.1111/j.1468-5914.1981.tb00033.x

Singh, A. K., & Singh, P. K. (2019). Digital Addiction: A conceptual overview. *Library Philosophy and Practice (E-Journal)*. https://digitalcommons.unl.edu/libphilprac/3538/

Singh, A., Halgamuge, M. N., & Moses, B. (2019). An Analysis of Demographic and Behavior Trends Using Social Media: Facebook, Twitter, and Instagram. *Social Network Analytics*, 87–108. https://doi.org/10.1016/B978-0-12-815458-8.00005-0

Singh, G. K., Lee, H., & Azuine, R. E. (2021). Growing Job-Related Income Losses, Increasing Social Inequalities, and Physical and Mental Health Impact During the COVID-19 Pandemic, United States, April – December 2020. *International Journal of Translational Medical Research and Public Health*, *5*(2), 76–89. https://doi.org/10.21106/ijtmrph.347

Sirois, F. M., & Pychyl, T. A. (2016). *Procrastination, Health, and Well-Being*. Academic Press. https://www.elsevier.com/books/procrastination-health-and-well-being/sirois/978-0-12-802862-9

Siste, K., Hanafi, E., Sen, L. T., Christian, H., Adrian, Siswidiani, L. P., Limawan, A. P., Murtani, B. J., & Suwartono, C. (2020). The impact of physical distancing and associated factors towards internet addiction among adults in Indonesia during COVID-19 pandemic: A nationwide web-based study. *Frontiers in Psychiatry*, *11*. https://doi.org/10.3389/fpsyt.2020.580977

Sistla, K. T., Rai, S., Praharaj, S. K., & Rege, S. (2022). The subjective experience of craving among individuals with alcohol dependence syndrome: A phenomenological study. *Journal of Substance Use*, *28*(6), 930–937. https://doi.org/10.1080/14659891.2022.2110953

Škare, M., Soriano, D. R., & Porada-Rochoń, M. (2020). Impact of COVID-19 on the travel and tourism industry. *Technological Forecasting and Social Change*, *163*(1), 120469. https://doi.org/10.1016/j.techfore.2020.120469

Slade-Silovic, O. (2018, June 26). *Why Video Content Works Better Than Text*. Covideo. https://www.covideo.com/why-video-content-works-better-than-text/

Small, D. M., Jones-Gotman, M., & Dagher, A. (2003). Feeding-induced dopamine release in dorsal striatum correlates with meal pleasantness ratings in healthy human volunteers. *NeuroImage*, *19*(4), 1709–1715. https://doi.org/10.1016/s1053-8119(03)00253-2

Small, G. W., Lee, J., Kaufman, A., Jalil, J., Siddarth, P., Gaddipati, H., Moody, T. D., & Bookheimer, S. Y. (2020). Brain health consequences of digital technology use. *Dialogues in Clinical Neuroscience*, *22*(2), 179–187. https://doi.org/10.31887/dcns.2020.22.2/gsmall

Smith, R. (2023, November 5). *Is TikTok replacing Google as No.1 search engine?* The Famuan. https://www.thefamuanonline.com/2023/11/05/is-tiktok-replacing-google-as-no-1-search-engine/

Smith, R. H. (2000). Assimilative and contrastive emotional reactions to upward and downward social comparisons. In *Handbook of Social Comparison* (pp. 173–200). Springer. https://doi.org/10.1007/978-1-4615-4237-7 10

Smith, T., & Short, A. (2022). Needs affordance as a key factor in likelihood of problematic social media use: Validation, latent Profile analysis and comparison of TikTok and Facebook problematic use measures. *Addictive Behaviors*, *129*(107259), 107259. https://doi.org/10.1016/j.addbeh.2022.107259

Smith, W. G. (2008). *Does gender influence online survey participation? A record-linkage analysis of university faculty online survey response behavior* [PhD Dissertation]. https://eric.ed.gov/?id=ED501717

Solà, A. (n.d.). *The impact of user-generated content (UGC) on TikTok*. Adsmurai. https://www.adsmurai.com/en/articles/the-impact-of-ugc-on-tiktok

Sona Systems. (2025). *Sona Systems: Cloud-based Subject Pool Software for Universities*. Sona Systems, Ltd. https://www.sona-systems.com/

prolsosi 🤍 🪐 [@misskaiixo]. (2024, April 3). *Try these tricks out for your upcoming exams to save HOURS of time!! 🤍 📔 #studytok #studywithme #studytips #Kilonotes #studytosuccess* [Video]. TikTok. https://www.tiktok.com/@misskaiixo/video/7353776805075045637

Şot, İ. (2022). Fostering intimacy on TikTok: a platform that "listens" and "creates a safe space." *Media, Culture & Society*, *44*(8), 016344372211047. https://doi.org/10.1177/01634437221104709

Şot, İ. (2023). Scrolling TikTok to soothe and foster self-care during the COVID-19 pandemic. *Social Media + Society*, *9*(4). https://doi.org/10.1177/20563051231213542

Southerton, C. (2021). Lip-Syncing and saving lives: Healthcare workers on TikTok. *International Journal of Communication*, *15*. https://ijoc.org/index.php/ijoc/article/view/16900

Steele, R. G., Khetawat, D., Christofferson, J. L., & Hall, J. A. (2022). Concurrent Validity of Self-Reported Social Media Use in Adolescents and Young Adults: Associations with Objective Data and Psychosocial Functioning. *Journal of Psychopathology and Behavioral Assessment*, *45*(1), 97–108. https://doi.org/10.1007/s10862-022-10013-9

Stefanone, M. A., Lackaff, D., & Rosen, D. (2011). Contingencies of self-worth and social-networking-site behavior. *Cyberpsychology, Behavior, and Social Networking*, *14*(1-2), 41–49. https://doi.org/10.1089/cyber.2010.0049

Steyn, R., & Ndofirepi, T. M. (2022). Structural validity and measurement invariance of the short version of the Big Five Inventory (BFI-10) in selected countries. *Cogent Psychology*, *9*(1). https://doi.org/10.1080/23311908.2022.2095035

Stokel-Walker, C. (2023). *TikTok Boom: The Inside Story of the World's Favourite App*. Canbury Press.

Storm, B. C., Stone, S. M., & Benjamin, A. S. (2016). Using the internet to access information inflates future use of the internet to access other information. *Memory*, *25*(6), 717–723. https://doi.org/10.1080/09658211.2016.1210171

Su, C., Zhou, H., Gong, L., Teng, B., Geng, F., & Hu, Y. (2021). Viewing personalized video clips recommended by TikTok activates default mode network and ventral tegmental area. *NeuroImage*, *237*(118136), 118136. https://doi.org/10.1016/j.neuroimage.2021.118136

Suler, J. (2004). The online disinhibition effect. *CyberPsychology & Behavior*, *7*(3), 321–326. https://doi.org/10.1089/1094931041291295

Suls, J., Martin, R., & Wheeler, L. (2002). Social comparison: Why, with whom, and with what effect? *Current Directions in Psychological Science*, *11*(5), 159–163. https://doi.org/10.1111/1467-8721.00191

Sweller, J. (2011). Cognitive load theory. In *Psychology of Learning and Motivation (Vol. 55)* (pp. 37–76). Academic Press. https://www.sciencedirect.com/science/article/abs/pii/B9780123876911000028

Syrjälä, M. (2024). *How social media uses UX design to keep user engaged - Case study: TikTok* [Bachelor's Thesis]. https://jyx.jyu.fi/handle/123456789/92809

Tanachot, S. (2021). *Factors influencing Thai digital content creators on content creation: A case of the TikTok platform* [Doctoral Dissertation]. https://archive.cm.mahidol.ac.th/handle/123456789/4314

The Culture Factor Group. (2025). *Country comparison tool*. The Culture Factor Group. Retrieved March 22, 2025, from https://www.theculturefactor.com/country-comparison-tool

Thelwall, M. (2008). Social networks, gender, and friending: An analysis of MySpace member profiles. *Journal of the American Society for Information Science and Technology*, *59*(8), 1321–1330. https://doi.org/10.1002/asi.20835

Thériault, R., Ben-Shachar, M. S., Patil, I., Lüdecke, D., Wiernik, B. M., & Makowski, D. (2024). Check your outliers! An introduction to identifying statistical outliers in R with easystats. *Behavior Research Methods*, *56*. https://doi.org/10.3758/s13428-024-02356-w

Thomala, L. L. (2024, February 29). *WeChat - statistics & facts*. Statista. https://www.statista.com/topics/9085/wechat/#topicOverview

Tian, X., Bi, X., & Chen, H. (2022). How short-form video features influence addiction behavior? Empirical research from the opponent process theory perspective. *Information Technology & People*, *36*(1). https://doi.org/10.1108/itp-04-2020-0186

TikTok Help Center. (2025). *Choosing between a private or public account*. TikTok Help Center. https://support.tiktok.com/en/account-and-privacy/account-privacy-settings/making-your-account-public-or-private

TikTok Help Center. (2025). *Duets*. TikTok Help Center. https://support.tiktok.com/en/using-tiktok/creating-videos/duets

Tran, B. X., Huong, L. T., Hinh, N. D., Nguyen, L. H., Le, B. N., Nong, V. M., Thuc, V. T. M., Tho, T. D., Latkin, C., Zhang, M. W., & Ho, R. C. (2017). A study on the influence of internet addiction and online interpersonal influences on health-related quality of life in young Vietnamese. *BMC Public Health*, *17*(1). https://doi.org/10.1186/s12889-016-3983-z

Triandis, H. C. (1995). *Individualism and collectivism*. Westview Press.

Triandis, H. C. (1999). Cross-cultural psychology. *Asian Journal of Social Psychology*, *2*(1), 127–143. https://doi.org/10.1111/1467-839x.00029

Tsai, W., & Ghoshal, S. (1998). Social capital and value creation: The role of intrafirm networks. *Academy of Management Journal*, *41*(4), 464–476. https://doi.org/10.5465/257085

Tuco, K. G., Castro-Diaz, S. D., Soriano-Moreno, D. R., & Benites-Zapata, V. A. (2023). Prevalence of nomophobia in university students: A systematic review and meta-analysis. *Healthcare Informatics Research*, *29*(1), 40–53. https://doi.org/10.4258%2Fhir.2023.29.1.40

Turel, O., & Cavagnaro, D. R. (2018). Effect of abstinence from social media on time perception: Differences between low- and at-risk for social media "addiction" groups. *Psychiatric Quarterly*, *90*(1). https://doi.org/10.1007/s11126-018-9614-3

Turkle, S. (2011). *Alone together: Why we expect more from technology and less from each other*. Basic Books.

Udayanga, S. (2023). Problematic internet use, nomophobia, and social media addiction. In *The Palgrave Handbook of Global Social Problems* (pp. 1–24). Palgrave Macmillan. https://doi.org/10.1007/978-3-030-68127-2 6-1

Uğur, N. G., & Başak, B. (2018). Intrinsic and extrinsic motivations of social media use: College students perspective. *The Online Journal of Quality in Higher Education*, *5*(3). https://www.tojqih.net/journals/tojqih/articles/v05i03/v05i03-10.pdf

Vaghefi, I., & Turel, O. (2024). Taking a Break from Social Media? A Multi-method Investigation of Social Media Abstinence Duration. *AIS Transactions on Human-Computer Interaction*, *16*(3), 309–338. https://doi.org/10.17705/1thci.00208

Valkenburg, P. M., van Driel, I. I., & Beyens, I. (2021). The associations of active and passive social media use with well-being: A critical scoping review. *New Media & Society*, *24*(2), 146144482110654. https://doi.org/10.1177/14614448211065425

Vallerand, R. J., & Ratelle, C. F. (2002). Intrinsic and extrinsic motivation: A hierarchical model. In *Handbook of Self-Determination Research* (pp. 37–63). University of Rochester Press.

Van Dijk, J. A. (2013). A theory of the digital divide. In *The Digital Divide* (pp. 49–72). Routledge.

Vaterlaus, J. M., Barnett, K., Roche, C., & Young, J. A. (2016). "Snapchat is more personal": An exploratory study on Snapchat behaviors and young adult interpersonal relationships. *Computers in Human Behavior*, *62*(62), 594–601. https://doi.org/10.1016/j.chb.2016.04.029

Vaterlaus, J. M., & Winter, M. (2021). TikTok: an exploratory study of young adults' uses and gratifications. *The Social Science Journal*, 1–20. https://doi.org/10.1080/03623319.2021.1969882

Vega, N. (2021, November 15). *This 31-year-old earns $120,000 a year from his TikTok side hustle*. CNBC. https://www.cnbc.com/2021/11/15/what-a-tiktok-star-earning-120000-a-year-spends-in-a-month.html

Verbeij, T., Pouwels, J. L., Beyens, I., & Valkenburg, P. M. (2021). The accuracy and validity of self-reported social media use measures among adolescents. *Computers in Human Behavior Reports*, *3*, 100090. https://doi.org/10.1016/j.chbr.2021.100090

Verduyn, P., Gugushvili, N., & Kross, E. (2021). The impact of social network sites on mental health: distinguishing active from passive use. *World Psychiatry*, *20*(1), 133–134. https://doi.org/10.1002/wps.20820

Verduyn, P., Gugushvili, N., Massar, K., Täht, K., & Kross, E. (2020). Social comparison on social networking sites. *Current Opinion in Psychology*, *36*(36), 32–37. https://doi.org/10.1016/j.copsyc.2020.04.002

Vigil, S. (2023). TikTok use, flow, and addictive behaviors. *McNair Summer Research Program*. 8. https://digital.sandiego.edu/mcnair-summer/8/

Villalonga-Olives, E., Adams, I., & Kawachi, I. (2016). The development of a bridging social capital questionnaire for use in population health research. *SSM - Population Health*, *2*(1), 613–622. https://doi.org/10.1016/j.ssmph.2016.08.008

Viñuela, E. (2022). "What's So Funny?": Videomemes and the circulation of contemporary music in social media. *Contemporary Music Review*, *41*(4), 1–14. https://doi.org/10.1080/07494467.2022.2087393

Vogel, E. A., & Rose, J. P. (2016). Self-reflection and interpersonal connection: Making the most of self-presentation on social media. *Translational Issues in Psychological Science*, *2*(3), 294–302. https://doi.org/10.1037/tps0000076

Vogels, E. A., Gelles-Watnick, R., & Massarat, N. (2022, August 10). *Teens, social media and technology 2022*. Pew Research Center. https://www.pewresearch.org/internet/2022/08/10/teens-social-media-and-technology-2022/

Wald, D. R., Gray, B. E., & Eatough, E. M. (2019). Surveys and web research. In *Advanced Research Methods for Applied Psychology: Design, Analysis and Reporting* (pp. 124–134). Routledge.

Wang, J. (2020). *From banning to regulating TikTok: Addressing concerns of national security, privacy, and online harms*. https://www.scribd.com/document/481065255/From-banning-to-regulating-TikTok-Addressing-concerns-of-national-security-privacy-and-online-harms

Wang, J., & Wang, S. (2025). The emotional reinforcement mechanism of and phased intervention strategies for social media addiction. *Behavioral Sciences*, *15*(5), 665–665. https://doi.org/10.3390/bs15050665

Wang, J.-L., Jackson, L. A., Zhang, D.-J., & Su, Z.-Q. (2012). The relationships among the Big Five Personality factors, self-esteem, narcissism, and sensation-seeking to Chinese University students' uses of social networking sites (SNSs). *Computers in Human Behavior*, *28*(6), 2313–2319. https://doi.org/10.1016/j.chb.2012.07.001

Wang, K., & Scherr, S. (2021). Dance the Night Away: How Automatic TikTok Use Creates Pre-Sleep Cognitive Arousal and Daytime Fatigue. *Mobile Media & Communication*, *10*(2), 205015792110561. https://doi.org/10.1177/20501579211056116

Wang, P. (2022). Recommendation Algorithm in TikTok: Strengths, Dilemmas, and Possible Directions. *International Journal of Social Science Studies*, *10*(5), 60. https://doi.org/10.11114/ijsss.v10i5.5664

Wang, T., Yeh, R. K.-J., Chen, C., & Tsydypov, Z. (2016). What drives electronic word-of-mouth on social networking sites? Perspectives of social capital and self-determination. *Telematics and Informatics*, *33*(4), 1034–1047. https://doi.org/10.1016/j.tele.2016.03.005

Watson, D., & Clark, L. A. (1997). Extraversion and Its Positive Emotional Core. In *Handbook of Personality Psychology* (pp. 767–793). Academic Press.

Wei, L. (2024). User-Generate-Content behaviours shape brand loyalty: A self-determination theory perspective. *6th International Conference on Informatization in Education, Management and Business (IEMB 2023)*, *27*. https://doi.org/10.54097/mzf86j96

Wei, S., Chen, X., & Liu, C. (2021). What motivates employees to use social media at work? A perspective of self-determination theory. *Industrial Management & Data Systems*, *ahead-of-print*(ahead-of-print). https://doi.org/10.1108/imds-06-2020-0322

Weimann, G., & Masri, N. (2020). Research Note: Spreading Hate on TikTok. *Studies in Conflict & Terrorism*, *46*(5), 1–14. https://doi.org/10.1080/1057610x.2020.1780027

West, B., Moore, H., & Barry, B. (2015). Beyond the tweet: Using Twitter to enhance engagement, learning, and success among first-year students. *Journal of Marketing Education*, *37*(3), 160–170. https://doi.org/10.1177/0273475315586061

Widiger, T. A. (2009). Neuroticism. In *Handbook of individual differences in social behavior* (pp. 129–146). The Guilford Press.

Wiederhold, B. K. (2022). BookTok made me do it: The evolution of reading. *Cyberpsychology, Behavior, and Social Networking*, *25*(3), 157–158. https://doi.org/10.1089/cyber.2022.29240.editorial

Wilcockson, T. D. W., Ellis, D. A., & Shaw, H. (2018). Determining typical smartphone usage: What data do we need? *Cyberpsychology, Behavior, and Social Networking*, *21*(6), 395–398. https://doi.org/10.1089/cyber.2017.0652

Wilmer, H. H., Sherman, L. E., & Chein, J. M. (2017). Smartphones and cognition: A review of research exploring the links between mobile technology habits and cognitive functioning. *Frontiers in Psychology*, *8*(605). https://doi.org/10.3389/fpsyg.2017.00605

Woolcock, M., & Sweetser, A. T. (2002). Bright ideas: Social capital—the bonds that connect. *ADB Review*, *34*(2), 26–27.

World Health Organisation. (2024, January). *ICD-11 for mortality and morbidity statistics*. World Health Organisation (WHO). https://icd.who.int/browse/2024-01/mms/en

Woszczynski, A. B., Roth, P. L., & Segars, A. H. (2002). Exploring the theoretical foundations of playfulness in computer interactions. *Computers in Human Behavior*, *18*(4), 369–388. https://doi.org/10.1016/s0747-5632(01)00058-9

Wright, C. (2017). Are Beauty Bloggers More Influential than Traditional Industry Experts? *Journal of Promotional Communications*, *5*(3), 303–322. https://promotionalcommunications.org/index.php/pc/article/view/113

Wuttaphan, N. (2022). Online Media Usage Behavior and Social Influence Factors Affecting Generation Zs' Self-Disclosure on Tiktok Application. *Muban Chombueng Rajabhat University Research Journal (Humanities and Social Science)*, *10*(1), 114–131.

Wyatt, K., & Phillips, J. G. (2005). Internet use and misuse in the workplace. *Proceedings of the 17th Australia Conference on Computer-Human Interaction: Citizens Online: Considerations for Today and the Future*, 1–4. https://dl.acm.org/doi/abs/10.5555/1108368.1108437

Xie, J., Xu, X., Zhang, Y., Tan, Y., Wu, D., Min, S., & Huang, H. (2023). The effect of short-form video addiction on undergraduates' academic procrastination: a moderated mediation model. *Frontiers in Psychology*, *14*. https://doi.org/10.3389/fpsyg.2023.1298361

Xie, W. (2014). Social network site use, mobile personal talk and social capital among teenagers. *Computers in Human Behavior*, *41*, 228–235. https://doi.org/10.1016/j.chb.2014.09.042

Xu, K., Tedrick, T., & Gold, J. A. (2023). Screen Use and Social Media "Addiction" in the Era of TikTok: What Generalists Should Know. *Missouri Medicine*, *120*(6), 440–445. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC10743327/

Xu, Y., Wang, J., & Ma, M. (2023). Adapting to lockdown: Exploring stress coping strategies on short video social media during the COVID-19 pandemic. *Psychology Research and Behavior Management*, *Volume 16*, 5273–5287. https://doi.org/10.2147/PRBM.S441744

Yang, L. H., Wong, L. Y., Grivel, M. M., & Hasin, D. S. (2017). Stigma and substance use disorders. *Current Opinion in Psychiatry*, *30*(5), 378–388. https://doi.org/10.1097/yco.0000000000000351

Yang, L. Y. (2021). Influence of social short videos on social capital of college students based on experimental analysis. *2nd International Conference on Information Science and Education (ICISE-IE)*, 801–805. https://doi.ieeecomputersociety.org/10.1109/ICISE-IE53922.2021.00183

Yang, Y. (2022). TikTok/Douyin Use and Its Influencer Video Use: A Cross-Cultural Comparison Between Chinese and US Users. *Online Media and Global Communication*, *0*(0). https://doi.org/10.1515/omgc-2022-0016

Yang, Y. (2023). Reasons for teenagers' habitual use of social media: A case study of TikTok. *SHS Web of Conferences*, *155*, 02006. https://doi.org/10.1051/shsconf/202315502006

Yang, Y., Adnan, H. M., & Sarmiti, N. Z. (2023). The relationship between anxiety and TikTok addiction among university students in China: Mediated by escapism and use intensity. *International Journal of Media and Information Literacy*, *8*(2), 458–464. https://doi.org/10.13187/ijmil.2023.2.458

Yang, Y., Liu, R.-D., Ding, Y., Lin, J., Ding, Z., & Yang, X. (2024). Time distortion for short-form video users. *Computers in Human Behavior*, *151*, 108009–108009. https://doi.org/10.1016/j.chb.2023.108009

Yao, M. (2021). Examination of Underlying Factors in Success of TikTok. *Proceedings of the 2021 International Conference on Enterprise Management and Economic Development (ICEMED 2021)*. https://www.atlantis-press.com/proceedings/icemed-21/125957312

Yao, N., Chen, J., Huang, S., Montag, C., & Elhai, J. D. (2023). Depression and social anxiety in relation to problematic TikTok use severity: The mediating role of boredom proneness and distress intolerance. *Computers in Human Behavior*, *145*, 107751. https://doi.org/10.1016/j.chb.2023.107751

Yaqi, Z., Lee, J.-Y., & Liu, S. (2021). Research on the Uses and Gratifications of Tiktok (Douyin short video). *International Journal of Contents*, *17*(1). https://doi.org/10.5392/IJoC.2021.17.1.037

Yardi-Schoenebeck, S., & Krupka, E. (n.d.). Misperceptions and misalignments: How young adults overestimate mobile phone use in everyday life. *Ann Arbor*, *1001*, 48103.

Zahn, M. (2025, January 19). *US bans TikTok. Here's what could come next.* ABC News. https://abcnews.go.com/Business/us-bans-tiktok/story?id=117743883

Zhang, T., Wang, W. Y. C., Lin, Y. C., & Tai, L.-H. (2014). Understanding user motivation for evaluating online content: a self-determination theory perspective. *Behaviour & Information Technology*, *34*(5), 479–491. https://doi.org/10.1080/0144929x.2014.964319

Zhang, X., Wu, Y., & Liu, S. (2019). Exploring short-form video application addiction: Socio-technical and attachment perspectives. *Telematics and Informatics*, *42*, 101243. https://doi.org/10.1016/j.tele.2019.101243

Zhang, Y., Liu, Y., Li, W., Peng, L., & Yuan, C. (2020). A study of the influencing factors of mobile social media fatigue behavior based on the grounded theory. *Information Discovery and Delivery*, *48*(2), 91–102. https://doi.org/10.1108/idd-11-2019-0084

Zhang, Y., Tang, L. S.-T., & Leung, L. (2011). Gratifications, collective self-esteem, online emotional openness, and traitlike communication apprehension as predictors of Facebook uses. *Cyberpsychology, Behavior, and Social Networking*, *14*(12), 733–739. https://doi.org/10.1089/cyber.2010.0042

Zhao, N., & Zhou, G. (2021). COVID-19 Stress and Addictive Social Media Use (SMU): Mediating Role of Active Use and Social Media Flow. *Frontiers in Psychiatry*, *12*. https://doi.org/10.3389/fpsyt.2021.635546

Zhao, W., Kelly, R. M., Rogerson, M. J., & Waycott, J. (2023). Older adults using technology for meaningful activities during COVID-19: An analysis through the lens of self-determination theory. *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*, 1–17. https://doi.org/10.1145/3544548.3580839

Zhao, Y. (2020). Analysis of TikTok's success based on its algorithm mechanism. *2020 International Conference on Big Data and Social Sciences (ICBDSS)*, 19–23. https://doi.org/10.1109/ICBDSS51270.2020.00012

Zheng, H., & Ling, R. (2021). Drivers of social media fatigue: A systematic review. *Telematics and Informatics*, *64*, 101696. https://doi.org/10.1016/j.tele.2021.101696

Appendix A

Participant Information sheet and 'Consent to Participate' statement

Participant Information Sheet

The title of the research project

Uses & gratifications, personality traits and individual differences in everyday TikTok use in the UK and USA.

What is the purpose of the research/questionnaire?

My name is Katy Bailey, and I am a postgraduate researcher in the Faculty of Science & Technology at Bournemouth University. I am conducting data collection as part of my masters research project.

TikTok is a video-based social media platform released by ByteDance in September 2016, specialising in short-form videos. TikTok is currently available in 39 languages across 150 countries and the most downloaded app in 2022. As a result, psychology literature surrounding TikTok has rapidly grown due to its emerging popularity. The Uses and Gratifications (U&G) Theory (Ruggiero, 2000) suggests that media use is encouraged and managed by psychological or social factors, with the goal of satisfying the user's needs and desires. So, this study aims to explore measures surrounding everyday TikTok usage across a variety of sociodemographic differences, personality traits, and motivational factors.

Why have I been invited?

Sona Systems: You have been invited to participate in this project through Bournemouth University's Sona Systems (www.sona-systems.com/). I am looking to recruit 100 students from the United Kingdom (UK) and United States (USA).

Prolific: You have been invited to participate in this project through Prolific (www.prolific.com/). I am looking to recruit 100 participants in a variety of age groups from the United Kingdom (UK) and United States (USA).

To participate, you must:

- Be a Bournemouth University student (*participants recruited via Sona only*)
- Have an active TikTok account *(active = accessed TikTok in the last 30 days)*
- Be aged 18 years or older
- Have UK or USA nationality
- Be fluent in English

Do I have to take part?
It is up to you to decide whether to take part in this study or not. If you do decide to take part, you will be able to download this information sheet to read in your own time. You can withdraw from participation at any time and without giving a reason, by closing the browser page.

Please note that once you have completed and submitted your survey responses, we are unable to remove your anonymised responses from the study as you will not be identifiable. Deciding to take part or not will not impact upon you, your studies at BU or current education, or day-to-day living.

How long will the online survey take to complete?
The survey should take approximately 15 minutes to complete.

What are the advantages and possible disadvantages or risks of taking part?
Whilst there are no immediate benefits for those people participating in the project, it is hoped that this work will provide further insight into the different motivational or sociodemographic factors which may contribute to TikTok usage.

Whilst we do not anticipate any risks to you in taking part in this study, you may refuse to continue the surveys by closing your browser. In the unlikely event that answering questions about your personality or TikTok usage might lead to minor distress or discomfort, please consider accessing one of the following support services:

- Health & Wellbeing support services (Bournemouth University): https://www.bournemouth.ac.uk/students/health-wellbeing/health-wellbeing-services
- Mind: www.mind.org.uk/need-urgent-help/using-this-tool/
- Samaritans: www.samaritans.org

What type of information will be sought from me and why is the collection of this information relevant for achieving the research project's objectives?
Information regarding your TikTok usage will be sought from you, as well as demographic information such as your age, gender, employment status, education level and nationality. This is relevant because this study aims to explore as many demographics as possible from the UK and USA and explore if there is a connection with these groups and TikTok usage to enhance future research.

Use of my information
Participation in this study is on the basis of consent: you do not have to complete the survey, and you can change your mind at any point before submitting the survey responses. We will use your data on the basis that it is necessary for the conduct of research, which is an activity in the

public interest. We put safeguards in place to ensure that your responses are kept secure and only used as necessary for this research study and associated activities such as a research audit.

Once you have submitted your survey response, it will not be possible for us to remove it from analysis because you will not be identifiable.

The anonymous information collected may be used to support other research projects in the future and access to it in this form will not be restricted. It will not be possible for you to be identified from this data. Anonymised data will be added to BU's Online Research Data Repository (a central location where data is stored) and which will be publicly available.

Contact for further information

If you have any questions or would like further information, please contact my supervisors:

- Professor John McAlaney, Lead Supervisor (jmcalaney@bournemouth.ac.uk)
- Dr Reece Bush-Evans (rbush@bournemouth.ac.uk).

In case of complaints:

Any concerns about the study should be directed to Professor Tiantian Zhang of the Faculty of Science & Technology, Bournemouth University by email to researchgovernance@bournemouth.ac.uk.

Consent to Participate:

Please indicate that you have read and understood the Participant Information Sheet for this research project and that you consent to take part in this questionnaire before continuing:

☐ I have read and understood the Participant Information Sheet and consent to take part in this questionnaire

☐ I do not consent to take part in this questionnaire [exit at this point]

Please indicate your agreement for the Research Team to access and use your recorded responses to this questionnaire before continuing:

☐ I give permission for members of the Research Team to have access to my anonymised responses. I understand that my anonymised responses may be reproduced in reports, academic publications and presentations but I will not be identified or identifiable.

☐ I understand that my data may be included in an anonymised form within a dataset to be archived at BU's Online Research Data Repository.

Appendix B

Complete list of survey questions

About you:

1. What is your age in years? *[Open text box – numerical values – range 18-100]*

2. What is your gender? *[Single option response]*
    a. Male / Female / Non-binary / Gender neutral / Third gender / Prefer not to say / Other/gender identity not listed [please specify]

3. Where are you from?
    a. United Kingdom (UK) / United States (USA)

4. What is the highest degree or level of education you have completed? If you are currently in education, select the previously highest degree received. *[Single option response]*
    a. Less than A-level or High School Diploma / A-Level or High School Diploma (or GED) / Associates Degree (AA, AS) / Bachelor's Degree (BA, BBA, BSc) / Master's Degree (MA, MSc, MEng, MRes) / Professional Degree (MD, DDS, JD, LLB) / Doctorate Degree (PhD, EdD) / Don't know/Not stated here

5. What is your current employment status? If more than one of these apply, choose the most relevant option, e.g., if you are a full-time student and are employed part-time, choose 'Student'. *[Single option response]*
    a. Employed full-time / Employed part-time / Unemployed (looking for work) / Unemployed (not looking for work) / Retired / Student (full-time or part-time) / Self-employed or Freelance / Not stated here

About your social media usage:

1. Which social media platforms do you use in addition to TikTok? Choose all that apply. *[Multiple option response]*
    a. Facebook / Twitter / Messenger / Instagram / Snapchat / Threads / Discord / BeReal / WhatsApp / YouTube / Other [please specify]

2. What is your current TikTok profile status?
    a. Public / Private

3. Approximately how long have you been using TikTok? *[single option response]*
    a. Less than a year / 1 year / 2 years / 3 years / 4 years / 5 years or more

4. How many TikTok followers do you have? Please write as a whole number, e.g. 12K followers = 12000 *[Open text box]*

5. How many TikTok accounts are you following? Please write as a whole number, e.g. 12K following = 12000 [*Open text box]*

6. How many likes does your TikTok profile have? Please write as a whole number, e.g. 12K likes = 12000 [*Open text box]*

7. How many TikTok profiles do you have?
    a. Just one / More than one

8. Do you use TikTok for business or self-promotion?
    a. Yes / No

9. Do you think your TikTok usage has changed since the COVID-19 lockdown? *[Single option response]*
    a. Increased / No change / Decreased / I did not use TikTok during the lockdown

About your TikTok usage:

1. How many hours do you **think** you spent on TikTok in the past week? *[Open text box - numerical values – range 0-168]*

2. How many times do you **think** you opened TikTok in the past week? *[Open text box - numerical values – range 0-1000]*

3. How many hours did you **actually** spend on TikTok in the past week in the day-time (6am-10pm)? *[Open text box - numerical values – range 0-168]*
    a. *Participant Instructions:* Go to your TikTok profile; Go to Settings and Privacy --> Screen time; Go to Summary and choose the previous week; Enter the number of hours from 'Time spent' --> Day-time

4. How many hours did you **actually** spend on TikTok in the past week at night-time (10pm-6am)? *[Open text box - numerical values – range 0-168]*
    a. *Participant Instructions:* Go to your TikTok profile; Go to Settings and Privacy --> Screen time; Go to Summary and choose the previous week; Enter the number of hours from 'Time spent' --> Night-time; Record in hours and minutes, e.g. 1 hour 42 minutes = 1.42

5. How many times did you **actually** open TikTok in the past week in the day-time (6am-10pm)? *[Open text box - numerical values – range 0-1000]*
    a. *Participant Instructions:* Go to your TikTok profile; Go to Settings and Privacy --> Screen time; Go to Summary and choose the previous week; Enter the number of times from 'App opened' --> Day-time; Record in hours and minutes, e.g. 1 hour 42 minutes = 1.42

6. How many times did you **actually** open TikTok in the past week at night-time (10pm-6am)? *[Open text box - numerical values – range 0-1000]*
    a. *Participant Instructions:* Go to your TikTok profile; Go to Settings and Privacy --> Screen time; Go to Summary and choose the previous week; Enter the number of times from 'App opened' --> Night-time

7. Were you surprised by the difference between what you thought and what your usage actually was? *[Single option response]*
    a. Not at all / I was a little surprised / I was very surprised

Big-Five Inventory-10 (BFI-10) (Rammstedt & John, 2007)

How well do the following statements describe your personality?

I see myself as someone who... [1 = Disagree strongly, 2 = Disagree a little, 3 = Neither agree nor disagree, 4 = Agree a little, 5 = Agree strongly]

1. is reserved
2. is generally trusting
3. tends to be lazy
4. is relaxed, handles stress well
5. has few artistic interests
6. is outgoing, sociable
7. tends to find fault with others
8. does a thorough job
9. gets nervous easily
10. has an active imagination

Motives for TikTok Use (Scherr & Wang, 2021)

I use TikTok (because) ... [1 = Totally disagree, 2 = Disagree, 3 = Neither agree nor disagree, 4 = Agree, 5 = Totally agree]

1. I can't stop using it
2. Filming and posting TikTok videos can show others that I am doing well
3. There are many new things on TikTok
4. I look great using TikTok's "beautify" feature function
5. It can be exciting
6. I can get "likes" from others by filming and posting TikTok videos
7. To forget unpleasant things from work, school, or life
8. It feels like an accomplishment to receive "likes" on my posted videos
9. When I don't want to work or study
10. It is exhilarating
11. To get to know new people
12. It gives me something to do to occupy my time with
13. Everybody else is using it
14. So that I can get a break from what I am doing
15. I can present myself to others through filming and posting TikTok videos
16. I enjoy filming videos on TikTok
17. Posting and sharing TikTok videos enhances interactions with families and friends
18. Filming and posting TikTok videos can get attention from others
19. It is cool

Appendix C

Debrief sheet

Uses & gratifications, personality traits and individual differences in everyday TikTok use in the UK and USA

Thank you very much for your time to take part in this research study.

In this study, you were asked to complete an online survey and asked questions about your social media usage, personality, demographics, and motives for TikTok use. Responses to these questions are very important to this study because this project hopes to understand possible connections between these factors and TikTok usage to enhance future research.

What is this study about?
TikTok is a social media platform released by ByteDance in September 2016, specialising in short-form videos. TikTok is currently available in 39 languages across 150 countries and the most downloaded app in 2022. As a result, psychology literature surrounding TikTok has rapidly grown. The Uses and Gratifications theory suggests that media use is encouraged and managed by psychological or social factors, with the goal of satisfying the user's needs and desires. So, this study aims to replicate measures designed to assess everyday TikTok usage in a UK and USA sample with potential influences from motives for use, demographic factors, and personality traits.

What are the aims of this study?
Your responses to the online survey will help us gain insight into unexplored aspects of everyday TikTok usage and future implications for TikTok in social media research.

What happens if I choose to withdraw from the study now?
As you have reached this stage, you have completed the survey, and your data is now anonymous and unidentifiable. Therefore, it will not be possible to remove your responses from analysis. Data will be stored for up to 5 years upon completion of the study, at which point it will be deleted.

If you have experienced discomfort or distress throughout this survey:
In the unlikely event that answering questions about your personality, social media use or TikTok usage has led to minor distress or discomfort, please consider accessing one of the following support services:

- Health & Wellbeing support services (*Bournemouth University*): https://www.bournemouth.ac.uk/students/health-wellbeing/health-wellbeing-services
- Mind: www.mind.org.uk/need-urgent-help/using-this-tool/
- Samaritans: www.samaritans.org

Contact Information

Should you have any further questions, please do not hesitate to contact myself or my supervisors:

- **Researcher**: Katy Bailey – kebailey@bournemouth.ac.uk
- **Supervisors**
  - Professor John McAlaney (Lead Supervisor) – jmcalaney@bournemouth.ac.uk
  - Dr Reece Bush-Evans – rbush@bournemouth.ac.uk

In case of complaints

Any concerns about the study should be directed to Professor Tiantian Zhang of the Faculty of Science & Technology, Bournemouth University by email to researchgovernance@bournemouth.ac.uk.

Appendix D

10-Item Big Five Inventory (BFI-10) scale and scoring instructions

Reference:

Rammstedt, B., & John, O. P. (2007). Measuring personality in one minute or less: A 10-item short version of the Big Five Inventory in English and German. *Journal of Research in Personality*, *41*(1), 203–212. https://doi.org/10.1016/j.jrp.2006.02.001

Questions extracted from the Big Five Inventory (BFI):

John, O. P., & Srivastava, S. (1999). The Big-Five trait taxonomy: History, measurement, and theoretical perspectives. In *Handbook of personality: Theory and research (Vol. 2)* (pp. 102–138). Guildford Press.

Instruction: How well do the following statements describe your personality?

Disagree strongly 1	Disagree a little 2	Neither agree nor disagree 3	Agree a little 4	Agree strongly 5

I see myself as someone who...

6. ...is reserved
22. ...is generally trusting
23. ...tends to be lazy
9. ...is relaxed, handles stress well
41. ...has few artistic interests
36. ...is outgoing, sociable
2. ...tends to find fault with others
3. ...does a thorough job
39. ...gets nervous easily
20. ...has an active imagination

Scoring:

BFI-10 scale scoring ("R" denotes reverse-scored items): *Maximum score = 10*

- Extraversion: 6R, 36
- Agreeableness: 2R, 22
- Conscientiousness: 3, 23R
- Neuroticism: 9R, 39
- Openness: 20, 41R

Appendix E

Motives for TikTok Use scale and scoring instructions

Reference:

Scherr, S., & Wang, K. (2021). Explaining the success of social media with gratification niches: Motivations behind daytime, nighttime, and active use of TikTok in China. *Computers in Human Behavior*, *124*, 106893. https://doi.org/10.1016/j.chb.2021.106893

Instruction: How well do the following statements describe your TikTok use?

Totally disagree	Disagree	Neither agree nor disagree	Agree	Totally agree
1	2	3	4	5

I use TikTok (because)...

1. I can't stop using it
2. Filming and posting TikTok videos can show others that I am doing well
3. There are many new things on TikTok
4. I look great using TikTok's "beautify" feature functions
5. It can be exciting
6. I can get "likes" from others by filming and posting TikTok videos
7. To forget unpleasant things from work, school, or life
8. It feels like an accomplishment to receive "likes" on my posted videos
9. When I don't want to work or study
10. It is exhilarating
11. To get to know new people
12. It gives me something to do to occupy my time with
13. Everybody else is using it
14. So that I can get a break from what I am doing
15. I can present myself to others through filming and posting TikTok videos
16. I enjoy filming videos on TikTok
17. Posting and sharing TikTok videos enhances interactions with families and friends
18. Filming and posting TikTok videos can get attention from others
19. It is cool

Scoring:

Motives for TikTok Use scale scoring (no items are reverse-scored): (*Maximum score in italics)*

- Socially Rewarding Self-Presentation: 2, 4, 6, 8, 11, 15, 16, 17, 18 *(45)*
- Trendiness: 5, 10, 13, 19 *(20)*
- Escapist Addiction: 1, 7, 9, 12, 14 *(25)*
- Novelty: 3 *(5)*

Appendix F

Frequency of SMP users interact with in addition to TikTok, compared by nationality.

	UK		USA	
Social media platform	***n* (261)**	**%**	***n* (100)**	**%**
Facebook	181	69.3	73	73.0
Twitter	125	47.9	54	54.0
Messenger	149	57.1	51	51.0
Instagram	244	93.5	83	83.0
Snapchat	160	61.3	49	49.0
Threads	19	7.3	5	5.0
Discord	62	23.8	41	41.0
BeReal	70	26.8	9	9.0
WhatsApp	227	87.0	34	34.0
YouTube	211	80.8	81	81.0
Other*	6	2.3	8	8.0

Notes: N = 361. *Defined as Pinterest, Reddit, LinkedIn, Tumblr, Bluesky, and Telegram Messenger

Appendix G

Descriptive statistics of participants' TikTok profiles and usage.

	UK		USA	
Variables	***n* (261)**	**%**	***n* (100)**	**%**
Profile Status				
Private	132	50.6	42	42.0
Public	129	49.4	58	58.0
Duration of Use				
Less than a year	17	6.5	0	0.0
1 year	20	7.7	7	7.0
2 years	60	23.0	24	24.0
3 years	69	26.4	32	32.0
4 years	53	20.3	26	26.0
5 years or more	42	16.1	11	11.0
Number of Profiles Level				
Just one	226	86.6	91	91.0
More than one	35	13.4	9	9.0
Used for Business Purposes				
Yes	22	8.4	7	7.0
No	239	91.6	93	93.0
Usage since the COVID-19 pandemic				
Increased	160	61.3	61	61.0
Decreased	37	14.2	17	17.0
No change	35	13.4	17	17.0
Did not use TikTok during the pandemic	29	11.1	5	5.0

Notes: N = 361

Appendix H

Paired samples t-test comparing TikTok use (in hours) between self-reported estimates and in-app recorded data

Paired Samples T-Test								
Measure 1		**Measure 2**	***t***	***df***	***p***	**Cohen's *d***	**SE Cohen's *d***
Estimate Hours	-	App Data Hours Total	10.159	360	< .001	0.535	0.063

Note. Student's t-test.

Test of Normality (Shapiro-Wilk)			***W***	***p***
Estimate Hours	-	App Data Hours Total	0.872	< .001

Note. Significant results suggest a deviation from normality.

Descriptives	***N***	**Mean**	***SD***	***SE***	**Coefficient of variation**
Estimate Hours	361	9.965	9.442	0.497	0.948
App Data Hours Total	361	4.976	6.811	0.358	1.369

Appendix I

Paired samples t-test comparing TikTok use (in number of times opened) between self-reported estimates and in-app recorded data

Paired Samples T-Test							
Measure 1		**Measure 2**	***t***	***df***	***p***	**Cohen's *d***	**SE Cohen's *d***
Estimate Times Opened	-	App Data Times Opened Total	-7.549	360	< .001	-0.397	0.066

Note. Student's t-test.

Test of Normality (Shapiro-Wilk)			***W***	***p***
Estimate Times Opened	-	App Data Times Opened Total	0.676	< .001

Note. Significant results suggest a deviation from normality.

Descriptives	***N***	**Mean**	***SD***	***SE***	**Coefficient of variation**
Estimate Times Opened	361	43.942	91.641	4.823	2.085
App Data Times Opened Total	361	89.443	98.372	5.177	1.100

Appendix J

Independent samples t-test comparing TikTok use (in hours) between younger and older users

Independent Samples T-Test	*t*	*df*	*p*	Cohen's *d*	SE Cohen's *d*
App Data Hours Total	-2.961	201.834	0.003	-0.337	0.122

Note. Welch's t-test.

Test of Normality (Shapiro-Wilk)		*W*	*p*
App Data Hours Total	Older	0.616	< .001
	Younger	0.772	< .001

Note. Significant results suggest a deviation from normality.

Test of Equality of Variances (Levene's)	*F*	df_1	df_2	*p*
App Data Hours Total	9.027	1	359	0.003

Group Descriptives	Group	*N*	Mean	*SD*	*SE*	Coefficient of variation
App Data Hours Total	Older	95	3.377	5.757	0.591	1.705
	Younger	266	5.548	7.073	0.434	1.275

Appendix K

Independent samples t-test comparing TikTok use (in number of times opened) between younger and older users

Independent Samples T-Test	*t*	*df*	*p*	Cohen's *d*	SE Cohen's *d*
App Data Times Opened Total	-5.841	269.996	< .001	-0.619	0.128

Note. Welch's t-test.

Test of Normality (Shapiro-Wilk)		*W*	*p*
App Data Times Opened Total	Older	0.712	< .001
	Younger	0.822	< .001

Note. Significant results suggest a deviation from normality.

Test of Equality of Variances (Levene's)	*F*	df_1	df_2	*p*
App Data Times Opened Total	18.562	1	359	< .001

Group Descriptives	Group	*N*	Mean	*SD*	*SE*	Coefficient of variation
App Data Times Opened Total	Older	95	49.874	64.256	6.593	1.288
	Younger	266	103.575	104.498	6.407	1.009

Appendix L

Independent samples t-test comparing TikTok use (in hours) between male and female users

Independent Samples T-Test	***t***	***df***	***p***	**Cohen's *d***	**SE Cohen's *d***
App Data Hours Total	2.604	179.812	0.010	0.303	0.122

Note. Welch's t-test.

Test of Normality (Shapiro-Wilk)		***W***	***p***
App Data Hours Total	Female	0.767	< .001
	Male	0.623	< .001

Note. Significant results suggest a deviation from normality.

Test of Equality of Variances (Levene's)	***F***	***df_1***	***df_2***	***p***
App Data Hours Total	5.409	1	359	0.021

Group Descriptives	**Group**	***N***	**Mean**	***SD***	***SE***	**Coefficient of variation**
App Data Hours Total	Female	270	5.474	7.010	0.427	1.281
	Male	91	3.500	5.979	0.627	1.708

Appendix M

Independent samples t-test comparing TikTok use (in number of times opened) between male and female users

Independent Samples T-Test	***t***	***df***	***p***	**Cohen's *d***	**SE Cohen's *d***
App Data Times Opened Total	0.830	158.551	0.408	0.100	0.121

Note. Welch's t-test.

Test of Normality (Shapiro-Wilk)		***W***	***p***
App Data Times Opened Total	Female	0.795	< .001
	Male	0.767	< .001

Note. Significant results suggest a deviation from normality.

Test of Equality of Variances (Levene's)	***F***	***df₁***	***df₂***	***p***
App Data Times Opened Total	1.427×10^{-7}	1	359	1.000

Group Descriptives	**Group**	***N***	**Mean**	***SD***	***SE***	**Coefficient of variation**
App Data Times Opened Total	Female	270	91.907	99.046	6.028	1.078
	Male	91	82.132	96.512	10.117	1.175

Appendix N

Independent samples t-test comparing TikTok use (in hours) between UK and USA users

Independent Samples T-Test	***t***	***df***	***p***	**Cohen's *d***	**SE Cohen's *d***
App Data Hours Total	5.427	279.630	< .001	0.575	0.120

Note. Welch's t-test.

Test of Normality (Shapiro-Wilk)		***W***	***p***
App Data Hours Total	UK	0.793	< .001
	USA	0.544	< .001

Note. Significant results suggest a deviation from normality.

Test of Equality of Variances (Levene's)	***F***	df_1	df_2	***p***
App Data Hours Total	33.901	1	359	< .001

Group Descriptives	**Group**	***N***	**Mean**	***SD***	***SE***	**Coefficient of variation**
App Data Hours Total	UK	261	5.945	7.260	0.449	1.221
	USA	100	2.447	4.620	0.462	1.888

Appendix O

Independent samples t-test comparing TikTok use (in number of times opened) between UK and USA users

Independent Samples T-Test	***t***	***df***	***p***	**Cohen's *d***	**SE Cohen's *d***
App Data Times Opened Total	1.977	217.928	0.049	0.222	0.118

Note. Welch's t-test.

Test of Normality (Shapiro-Wilk)		***W***	***p***
App Data Times Opened Total	UK	0.801	< .001
	USA	0.782	< .001

Note. Significant results suggest a deviation from normality.

Test of Equality of Variances (Levene's)	***F***	df_1	df_2	***p***
App Data Times Opened Total	3.487	1	359	0.063

Group Descriptives	**Group**	***N***	**Mean**	***SD***	***SE***	**Coefficient of variation**
App Data Times Opened Total	UK	261	95.218	102.894	6.369	1.081
	USA	100	74.370	84.065	8.407	1.130

Appendix P

Means, standard deviations, skewness, and kurtosis for all predictor variables.

Predictors	*M*	*SD*	Skewness	Kurtosis
Demographic Factors				
Age	28.72	10.42	1.23	1.05
Gender	1.25	0.44	1.15	-0.69
Nationality	1.28	0.45	1.00	-1.00
Personality Traits				
Extraversion	5.92	2.04	0.00	-0.60
Agreeableness	6.95	1.83	-0.42	-0.39
Conscientiousness	7.20	1.65	-0.21	-0.37
Neuroticism	6.62	2.07	-0.18	-0.90
Openness	7.12	1.74	-0.26	-0.05
Motives for Use				
Socially Rewarding Self-Presentation	19.50	8.08	0.60	-0.23
Trendiness	13.19	2.74	-0.32	0.36
Escapist Addiction	18.57	3.39	-0.44	0.28
Novelty	3.81	0.95	-1.11	1.24

Appendix Q

Means, standard deviations, minimum, maximum, skewness, and kurtosis for outcome variables, compared by day-time, night-time and total.

Outcome Variables	*M*	*SD*	Skewness	Kurtosis	Minimum	Maximum
Hours spent on TikTok						
Day-time	3.16	4.50	1.78	2.55	0	23
Night-time	1.82	2.95	2.26	5.24	0	15.5
Total	4.98	6.81	1.68	2.24	0	31.92
Times TikTok was opened						
Day-time	64.71	72.50	1.81	3.59	0	400
Night-time	24.74	35.26	3.00	12.84	0	265
Total	89.44	98.37	1.98	4.74	0	587

Appendix R

Zero-order Pearson correlations among predictor variables.

	2	3	4	5	6	7	8	9	10	11	12
1	-.01	-.15**	.00	.04	.14**	-.17**	.02	.13*	.02	-.16**	.14**
2	--	.04	-.06	.05	.06	.34***	-.04	.00	.10	.23***	.09
3		--	.11*	.06	.02	.09	-.17**	.01	.00	-.03	-.14**
4			--	.29***	.15**	-.37***	.10	.14**	.10	-.04	.05
5				--	.07	-.20***	.12*	.13*	.13*	-.01	.12*
6					--	-.18***	.05	.12*	.06	-.10	.13*
7						--	.04	-.11*	.00	.22***	.02
8							--	-.04	.00	-.03	.11*
9								--	.45***	.13*	.18***
10									--	.44***	.39***
11										--	.29***
12											--

Note. *$p < .05$; **$p < .01$; ***$p < .001$; $N = 361$. **Demographic Factors:** 1=Age; 2=Gender; 3=Nationality; **Personality Traits:** 4=Extraversion; 5=Agreeableness; 6=Conscientiousness; 7=Neuroticism; 8=Openness; **Motives for TikTok Use:** 9=Socially Rewarding Self-Presentation; 10=Trending; 11=Escapist Addiction; 12=Novelty.

Appendix S

Hierarchical regression results for the number of hours spent on TikTok in the past week during day-time (6am-10pm): Block 1 (demographic factors)

Model Summary - App Data Hours Day

										Durbin-Watson		
Model	R	R^2	Adjusted R^2	RMSE	R^2 Change	F Change	df1	df2	p	Autocorrelation	Statistic	p
H_0	0.263	0.069	0.061	4.362	0.069	8.823	3	357	< .001	0.223	1.536	< .001

Note. Null model includes Age, Gender, Nationality

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_0	Regression	503.662	3	167.887	8.823	< .001
	Residual	6793.026	357	19.028		
	Total	7296.688	360			

Note. Null model includes Age, Gender, Nationality

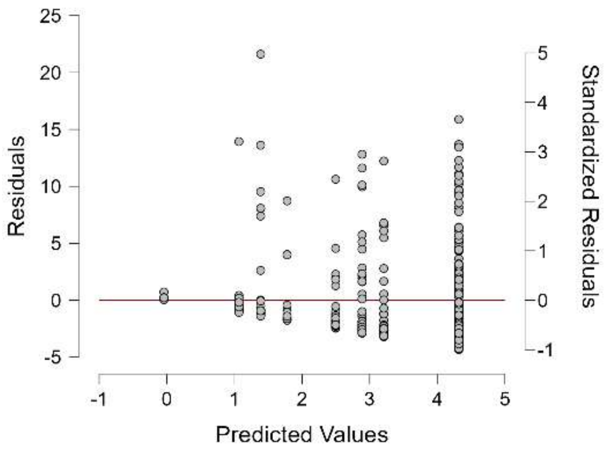
Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p
H_0	(Intercept)	-0.042	0.681		-0.061	0.951
	Age	1.109	0.524	0.109	2.117	0.035
	Gender	1.430	0.529	0.138	2.702	0.007
	Nationality	1.821	0.516	0.181	3.532	< .001

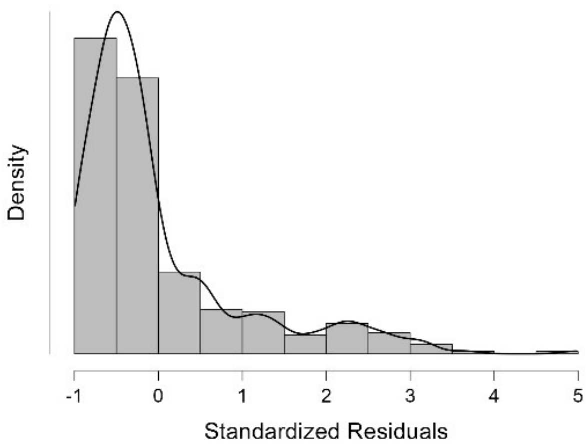
Coefficients Covariance Matrix

Model		Age	Gender	Nationality
H_0	Age	0.274	0.005	-0.026
	Gender		0.280	-0.011
	Nationality			0.266

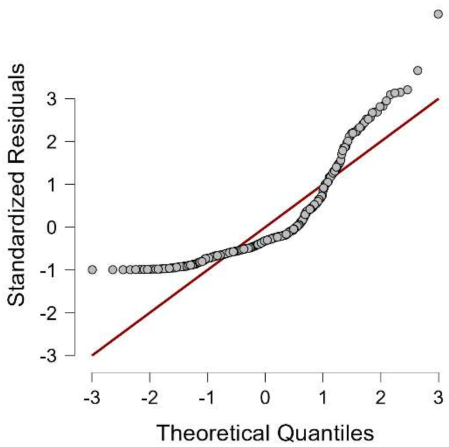
Residuals vs. Predicted



Standardized Residuals Histogram



Q-Q Plot Standardized Residuals



Appendix T

Hierarchical regression results for the number of hours spent on TikTok in the past week during day-time (6am-10pm): Block 2 (personality traits)

Model Summary - App Data Hours Day

										Durbin-Watson		
Model	R	R^2	Adjusted R^2	RMSE	R^2 Change	F Change	df1	df2	p	Autocorrelation	Statistic	p
H_0	0.235	0.055	0.042	4.407	0.055	4.156	5	355	0.001	0.271	1.443	< .001
H_1	0.319	0.102	0.081	4.316	0.046	6.038	3	352	< .001	0.225	1.535	< .001

Note. Null model includes Extraversion, Agreeableness, Conscientiousness, Neuroticism, Openness

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_0	Regression	403.505	5	80.701	4.156	0.001
	Residual	6893.183	355	19.417		
	Total	7296.688	360			
H_1	Regression	740.844	8	92.605	4.972	< .001
	Residual	6555.844	352	18.625		
	Total	7296.688	360			

Note. Null model includes Extraversion, Agreeableness, Conscientiousness, Neuroticism, Openness

Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p
H_0	(Intercept)	3.019	1.984		1.522	0.129
	Extraversion	0.202	0.127	0.091	1.588	0.113
	Agreeableness	0.255	0.134	0.103	1.896	0.059
	Conscientiousness	-0.285	0.144	-0.104	-1.980	0.048
	Neuroticism	0.295	0.123	0.136	2.399	0.017
	Openness	-0.383	0.135	-0.148	-2.829	0.005
H_1	(Intercept)	1.897	1.983		0.956	0.340
	Age	1.081	0.525	0.106	2.058	0.040

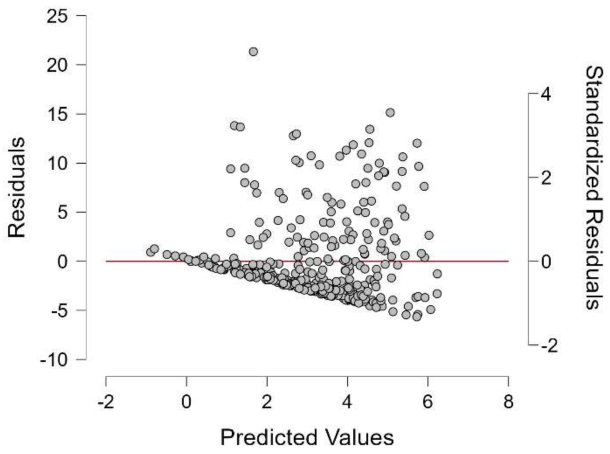
Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p
	Gender	1.307	0.570	0.126	2.295	0.022
	Nationality	1.519	0.530	0.151	2.868	0.004
	Extraversion	0.116	0.126	0.052	0.917	0.360
	Agreeableness	0.207	0.133	0.084	1.556	0.121
	Conscientiousness	-0.323	0.143	-0.118	-2.264	0.024
	Neuroticism	0.095	0.133	0.044	0.718	0.473
	Openness	-0.286	0.136	-0.111	-2.105	0.036

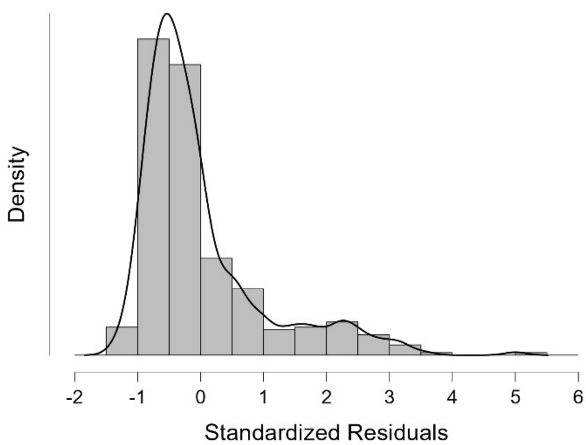
Coefficients Covariance Matrix

Model		Extraversion	Agreeableness	Conscientiousness	Neuroticism	Openness	Age	Gender	Nationality
H_0	Extraversion	0.016	-0.004	-0.001	0.005	-0.002			
	Agreeableness		0.018	-1.441×10^{-4}	0.002	-0.002			
	Conscientiousness			0.021	0.002	-9.349×10^{-4}			
	Neuroticism				0.015	-0.002			
	Openness					0.018			
H_1	Extraversion	-0.003	0.004	0.005	-0.007	-0.003	0.276	0.013	-0.025
	Agreeableness		-0.009	-0.011	-0.029	0.007	0.013	0.324	0.008
	Conscientiousness			-0.003	-0.011	0.015	-0.025	0.008	0.281
	Neuroticism				0.006	-0.002	-0.003	-0.004	-0.010
	Openness					-0.002	0.004	-0.009	-0.005
	Age						0.005	-0.011	-0.003
	Gender							-0.029	-0.011
	Nationality								0.015

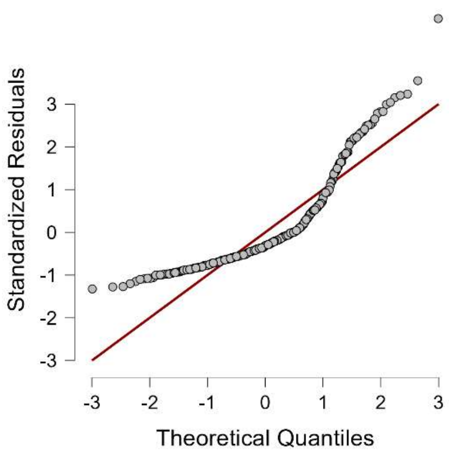
Residuals vs. Predicted



Standardized Residuals Histogram



Q-Q Plot Standardized Residuals



Appendix U

Hierarchical regression results for the number of hours spent on TikTok in the past week during day-time (6am-10pm): Block 3 (motives for TikTok use)

Model Summary - App Data Hours Day

										Durbin-Watson		
Model	R	R^2	Adjusted R^2	RMSE	R^2 Change	F Change	df1	df2	p	Autocorrelation	Statistic	p
H_0	0.152	0.023	0.012	4.475	0.023	2.101	4	356	0.080	0.298	1.389	< .001
H_1	0.333	0.111	0.080	4.318	0.088	4.288	8	348	< .001	0.243	1.499	< .001

Note. Null model includes Socially rewarding self-presentation, Trendiness, Escapist addiction, Novelty

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_0	Regression	168.305	4	42.076	2.101	0.080
	Residual	7128.383	356	20.024		
	Total	7296.688	360			
H_1	Regression	807.867	12	67.322	3.611	< .001
	Residual	6488.821	348	18.646		
	Total	7296.688	360			

Note. Null model includes Socially rewarding self-presentation, Trendiness, Escapist addiction, Novelty

Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p
H_0	(Intercept)	-0.183	1.524		-0.120	0.904
	Socially rewarding self-presentation	0.018	0.033	0.031	0.534	0.593
	Trendiness	0.063	0.111	0.038	0.568	0.570
	Escapist addiction	0.175	0.078	0.132	2.236	0.026
	Novelty	-0.285	0.274	-0.060	-1.040	0.299
H_1	(Intercept)	-0.265	2.348		-0.113	0.910
	Age	1.069	0.543	0.105	1.970	0.050

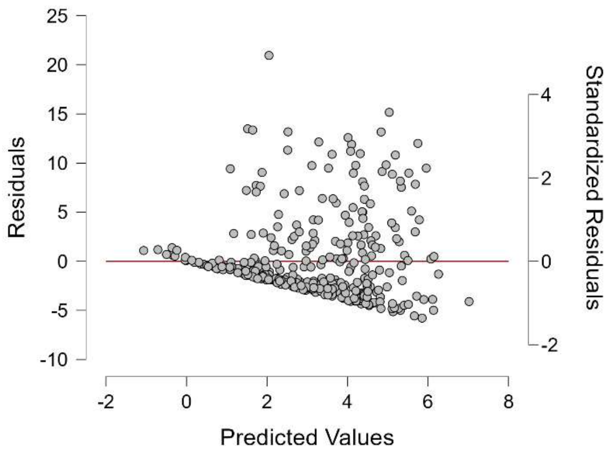
Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p
	Gender	1.167	0.580	0.113	2.013	0.045
	Nationality	1.576	0.536	0.157	2.941	0.003
	Extraversion	0.095	0.127	0.043	0.747	0.455
	Agreeableness	0.186	0.135	0.076	1.385	0.167
	Conscientiousness	-0.326	0.145	-0.119	-2.241	0.026
	Neuroticism	0.073	0.134	0.033	0.541	0.589
	Openness	-0.269	0.137	-0.104	-1.965	0.050
	Socially rewarding self-presentation	0.028	0.032	0.050	0.856	0.393
	Trendiness	0.028	0.108	0.017	0.262	0.793
	Escapist addiction	0.084	0.081	0.064	1.044	0.297
	Novelty	0.018	0.276	0.004	0.065	0.948

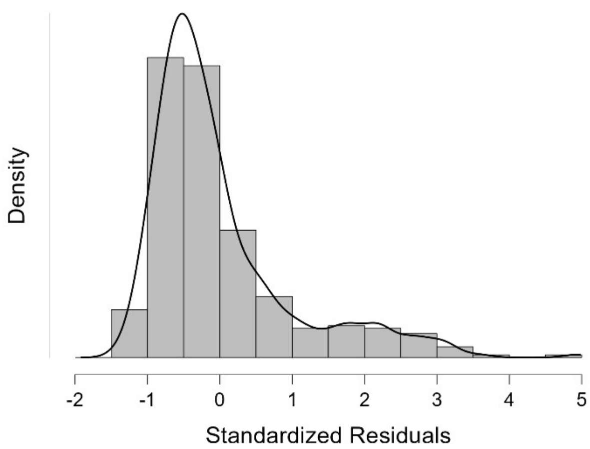
Coefficients Covariance Matrix

Model		Socially rewarding self-presentation	Trendiness	Escapist addiction	Novelty	Age	Gender	Nationality	Extraversion	Agreeableness	Conscientiousness	Neuroticism	Openness
H_0	Socially rewarding self-presentation	0.001	-0.002	2.130×10^{-4}	-1.704×10^{-4}								
	Trendiness		0.012	-0.003	-0.008								
	Escapist addiction			0.006	-0.003								
	Novelty				0.075								
H_1	Socially rewarding self-presentation	0.003	-0.002	-0.007	0.022	0.294	0.022	-0.023	-0.004	0.002	0.001	-0.006	-0.004
	Trendiness		-7.858×10^{-4}	-0.007	-5.548×10^{-4}	0.022	0.336	0.003	-0.004	-0.009	-0.012	-0.027	0.006
	Escapist addiction			0.002	0.019	-0.023	0.003	0.287	-0.010	-0.006	-0.004	-0.012	0.015
	Novelty				-4.438×10^{-4}	-0.004	-0.004	-0.010	0.016	-0.003	-0.001	0.006	-0.002
	Age					0.002	-0.009	-0.006	-0.003	0.018	6.873×10^{-4}	0.003	-0.002
	Gender						-0.012	-0.004	-0.001	6.873×10^{-4}	0.021	0.003	-0.001
	Nationality							-0.012	0.006	0.003	0.003	0.018	-0.003
	Extraversion								-0.002	-0.002	-0.001	-0.003	0.019
	Agreeableness									-1.923×10^{-4}	-3.541×10^{-4}	1.138×10^{-4}	2.422×10^{-4}
	Conscientiousness										-2.303×10^{-4}	3.862×10^{-4}	-2.558×10^{-5}
	Neuroticism											-0.001	7.271×10^{-4}
	Openness												-0.003

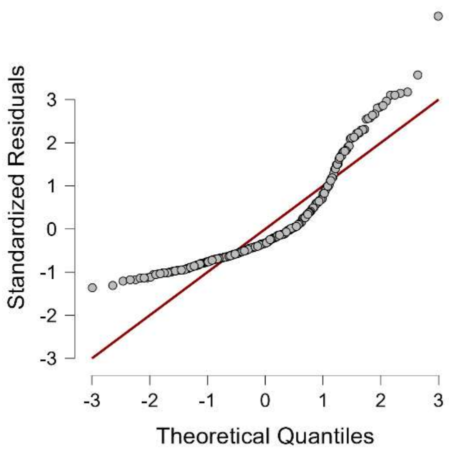
Residuals vs. Predicted



Standardized Residuals Histogram



Q-Q Plot Standardized Residuals



Appendix V

Hierarchical regression results for the number of hours spent on TikTok in the past week during night-time (10pm-6am): Block 1 (demographic factors)

Model Summary - App Data Hours Night

										Durbin-Watson		
Model	R	R^2	Adjusted R^2	RMSE	R^2 Change	F Change	df1	df2	p	Autocorrelation	Statistic	p
H_0	0.266	0.071	0.063	2.854	0.071	9.035	3	357	< .001	0.151	1.658	< .001

Note. Null model includes Age, Gender, Nationality

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_0	Regression	220.765	3	73.588	9.035	< .001
	Residual	2907.701	357	8.145		
	Total	3128.465	360			

Note. Null model includes Age, Gender, Nationality

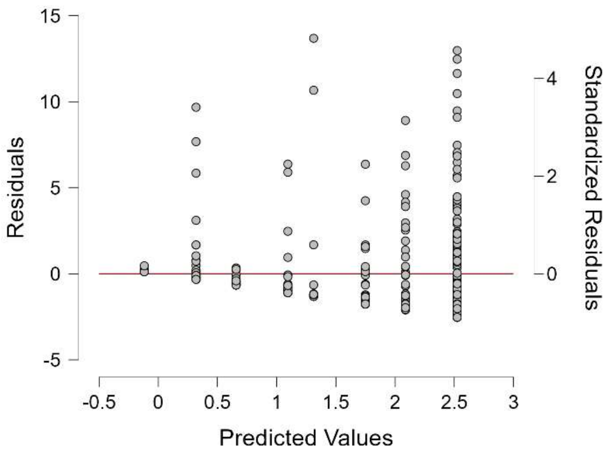
Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p
H_0	(Intercept)	-0.118	0.445		-0.265	0.791
	Age	0.776	0.343	0.116	2.264	0.024
	Gender	0.437	0.346	0.064	1.263	0.208
	Nationality	1.431	0.337	0.217	4.240	< .001

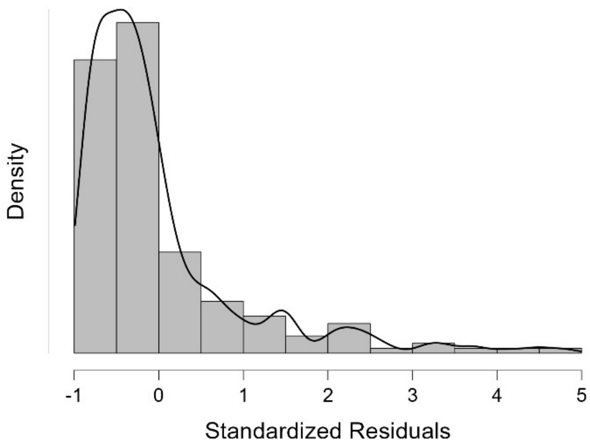
Coefficients Covariance Matrix

Model		Age	Gender	Nationality
H_0	Age	0.117	0.002	-0.011
	Gender		0.120	-0.005
	Nationality			0.114

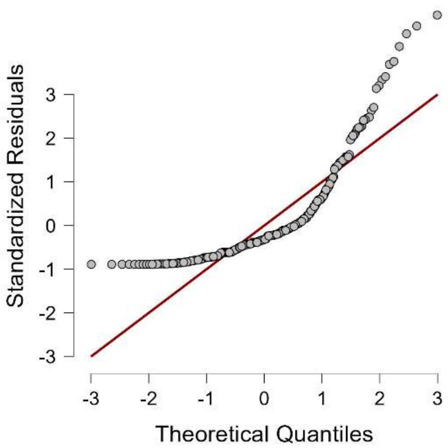
Residuals vs. Predicted



Standardized Residuals Histogram



Q-Q Plot Standardized Residuals



Appendix W

Hierarchical regression results for the number of hours spent on TikTok in the past week during night-time (6am-10pm): Block 2 (personality traits)

Model Summary - App Data Hours Night

										Durbin-Watson		
Model	**R**	**R^2**	**Adjusted R^2**	**RMSE**	**R^2 Change**	**F Change**	**df1**	**df2**	**p**	**Autocorrelation**	**Statistic**	**p**
H_0	0.209	0.044	0.030	2.903	0.044	3.230	5	355	0.007	0.192	1.582	< .001
H_1	0.307	0.094	0.074	2.837	0.051	6.605	3	352	< .001	0.128	1.704	0.004

Note. Null model includes Extraversion, Agreeableness, Conscientiousness, Neuroticism, Openness

ANOVA

Model		**Sum of Squares**	**df**	**Mean Square**	**F**	**p**
H_0	Regression	136.135	5	27.227	3.230	0.007
	Residual	2992.330	355	8.429		
	Total	3128.465	360			
H_1	Regression	295.604	8	36.951	4.591	< .001
	Residual	2832.861	352	8.048		
	Total	3128.465	360			

Note. Null model includes Extraversion, Agreeableness, Conscientiousness, Neuroticism, Openness

Coefficients

Model		**Unstandardized**	**Standard Error**	**Standardized**	**t**	**p**
H_0	(Intercept)	1.981	1.307		1.516	0.130
	Extraversion	0.180	0.084	0.124	2.151	0.032
	Agreeableness	0.089	0.089	0.055	1.011	0.313
	Conscientiousness	-0.162	0.095	-0.091	-1.710	0.088
	Neuroticism	0.150	0.081	0.106	1.853	0.065
	Openness	-0.236	0.089	-0.140	-2.651	0.008
H_1	(Intercept)	1.030	1.304		0.790	0.430
	Age	0.756	0.345	0.113	2.189	0.029

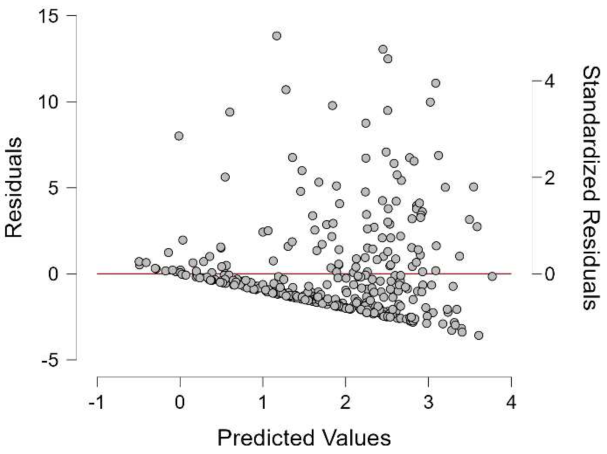
Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p
	Gender	0.399	0.374	0.059	1.065	0.288
	Nationality	1.242	0.348	0.189	3.567	< .001
	Extraversion	0.119	0.083	0.082	1.433	0.153
	Agreeableness	0.067	0.087	0.042	0.770	0.442
	Conscientiousness	-0.173	0.094	-0.097	-1.850	0.065
	Neuroticism	0.048	0.087	0.034	0.548	0.584
	Openness	-0.170	0.089	-0.100	-1.900	0.058

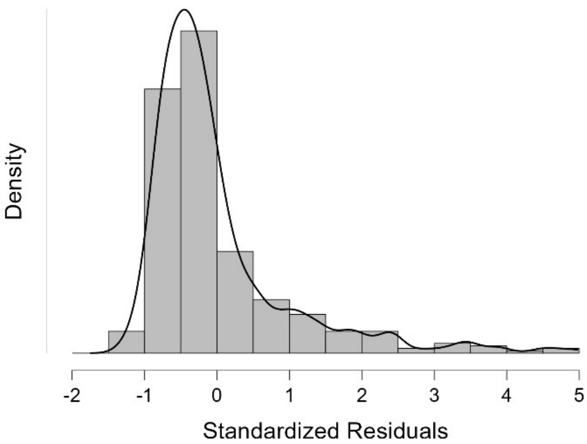
Coefficients Covariance Matrix

Model		Extraversion	Agreeableness	Conscientiousness	Neuroticism	Openness	Age	Gender	Nationality
H_0	Extraversion	0.007	-0.002	-6.321×10^{-4}	0.002	-7.206×10^{-4}			
	Agreeableness		0.008	-6.254×10^{-5}	8.455×10^{-4}	-7.921×10^{-4}			
	Conscientiousness			0.009	0.001	-4.058×10^{-4}			
	Neuroticism				0.007	-7.487×10^{-4}			
	Openness					0.008			
H_1	Extraversion	-0.001	0.002	0.002	-0.003	-0.001	0.119	0.006	-0.011
	Agreeableness		-0.004	-0.005	-0.012	0.003	0.006	0.140	0.003
	Conscientiousness			-0.001	-0.005	0.006	-0.011	0.003	0.121
	Neuroticism				0.002	-9.382×10^{-4}	-0.001	-0.002	-0.004
	Openness					-9.740×10^{-4}	0.002	-0.004	-0.002
	Age						0.002	-0.005	-0.001
	Gender							-0.012	-0.005
	Nationality								0.006

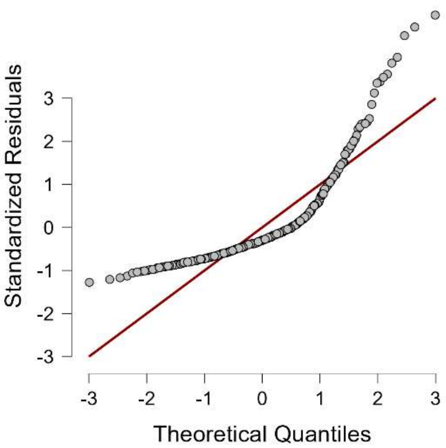
Residuals vs. Predicted



Standardized Residuals Histogram



Q-Q Plot Standardized Residuals



Appendix X

Hierarchical regression results for the number of hours spent on TikTok in the past week during night-time (6am-10pm): Block 3 (motives for TikTok use)

Model Summary - App Data Hours Night

										Durbin-Watson		
Model	**R**	**R^2**	**Adjusted R^2**	**RMSE**	**R^2 Change**	**F Change**	**df1**	**df2**	**p**	**Autocorrelation**	**Statistic**	**p**
H_0	0.097	0.010	-0.002	2.950	0.010	0.854	4	356	0.492	0.235	1.499	< .001
H_1	0.317	0.100	0.069	2.844	0.091	4.395	8	348	< .001	0.137	1.688	0.002

Note. Null model includes Socially rewarding self-presentation, Trendiness, Escapist addiction, Novelty

ANOVA

Model		**Sum of Squares**	**df**	**Mean Square**	**F**	**p**
H_0	Regression	29.726	4	7.431	0.854	0.492
	Residual	3098.740	356	8.704		
	Total	3128.465	360			
H_1	Regression	314.081	12	26.173	3.236	< .001
	Residual	2814.384	348	8.087		
	Total	3128.465	360			

Note. Null model includes Socially rewarding self-presentation, Trendiness, Escapist addiction, Novelty

Coefficients

Model		**Unstandardized**	**Standard Error**	**Standardized**	**t**	**p**
H_0	(Intercept)	0.797	1.005		0.794	0.428
	Socially rewarding self-presentation	0.022	0.022	0.059	0.997	0.320
	Trendiness	0.009	0.073	0.008	0.123	0.902
	Escapist addiction	0.060	0.052	0.069	1.153	0.250
	Novelty	-0.165	0.181	-0.053	-0.914	0.361
H_1	(Intercept)	0.416	1.547		0.269	0.788
	Age	0.830	0.357	0.124	2.322	0.021

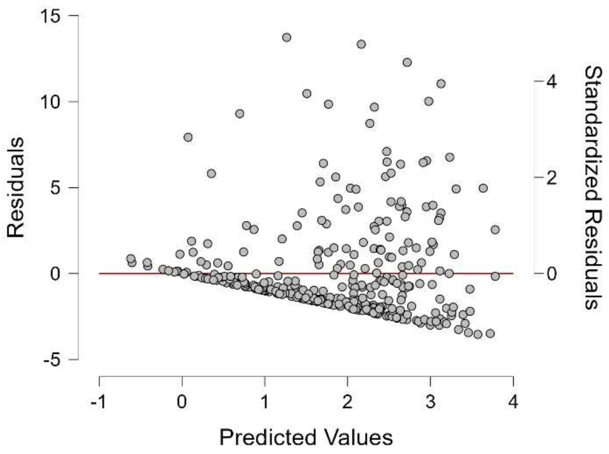
Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p
	Gender	0.383	0.382	0.057	1.004	0.316
	Nationality	1.266	0.353	0.192	3.585	< .001
	Extraversion	0.107	0.084	0.074	1.283	0.200
	Agreeableness	0.055	0.089	0.034	0.616	0.538
	Conscientiousness	-0.187	0.096	-0.105	-1.958	0.051
	Neuroticism	0.045	0.088	0.032	0.510	0.611
	Openness	-0.164	0.090	-0.097	-1.815	0.070
	Socially rewarding self-presentation	0.028	0.021	0.077	1.311	0.191
	Trendiness	-0.016	0.071	-0.015	-0.227	0.821
	Escapist addiction	0.011	0.053	0.012	0.200	0.842
	Novelty	0.067	0.182	0.021	0.369	0.713

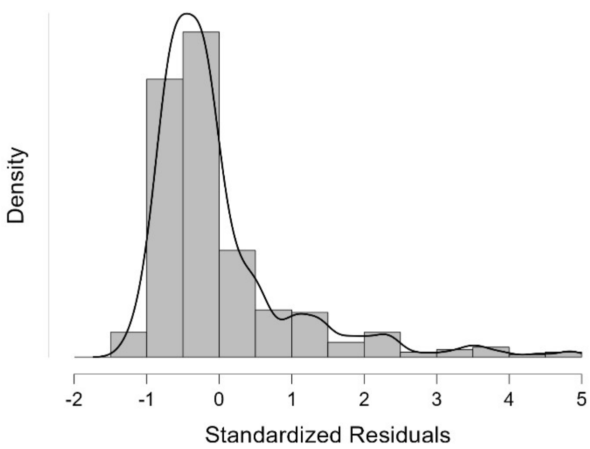
Coefficients Covariance Matrix

Model		Socially rewarding self-presentation	Trendiness	Escapist addiction	Novelty	Age	Gender	Nationality	Extraversion	Agreeableness	Conscientiousness	Neuroticism	Openness
H_0	Socially rewarding self-presentation	4.688×10^{-4}	-6.653×10^{-4}	9.257×10^{-5}	-7.407×10^{-5}								
	Trendiness		0.005	-0.001	-0.004								
	Escapist addiction			0.003	-0.001								
	Novelty				0.033								
H_1	Socially rewarding self-presentation	0.001	-0.001	-0.003	0.009	0.128	0.010	-0.010	-0.002	0.001	5.548×10^{-4}	-0.002	-0.002
	Trendiness		-3.408×10^{-4}	-0.003	-2.406×10^{-4}	0.010	0.146	0.001	-0.002	-0.004	-0.005	-0.012	0.003
	Escapist addiction			8.886×10^{-4}	0.008	-0.010	0.001	0.125	-0.004	-0.003	-0.002	-0.005	0.006
	Novelty				-1.925×10^{-4}	-0.002	-0.002	-0.004	0.007	-0.001	-4.558×10^{-4}	0.002	-9.766×10^{-4}
	Age					0.001	-0.004	-0.003	-0.001	0.008	2.981×10^{-4}	0.001	-9.538×10^{-4}
	Gender						-0.005	-0.002	-4.558×10^{-4}	2.981×10^{-4}	0.009	0.001	-4.785×10^{-4}
	Nationality							-0.005	0.002	0.001	0.001	0.008	-0.001
	Extraversion								-9.766×10^{-4}	-9.538×10^{-4}	-4.785×10^{-4}	-0.001	0.008
	Agreeableness									-8.342×10^{-5}	-1.536×10^{-4}	4.935×10^{-5}	1.051×10^{-4}
	Conscientiousness										-9.989×10^{-5}	1.675×10^{-4}	-1.110×10^{-5}
	Neuroticism											-6.088×10^{-4}	3.153×10^{-4}
	Openness												-0.001

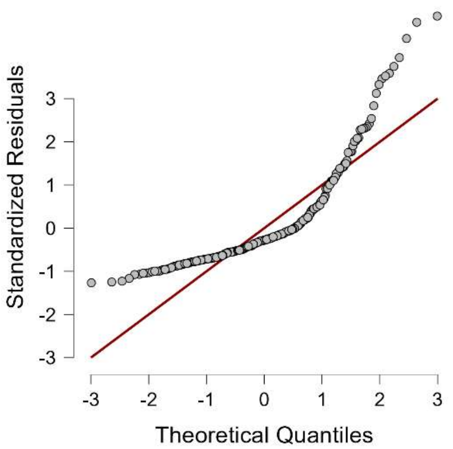
Residuals vs. Predicted



Standardized Residuals Histogram



Q-Q Plot Standardized Residuals



Appendix Y

Hierarchical regression results for the number of hours spent on TikTok in the past week in total: Block 1 (demographic factors)

Hours Total Block 1: Demographics

Model Summary - App Data Hours Total

										Durbin-Watson		
Model	R	R^2	Adjusted R^2	RMSE	R^2 Change	F Change	df1	df2	p	Autocorrelation	Statistic	p
H_0	0.285	0.081	0.074	6.556	0.081	10.546	3	357	< .001	0.241	1.498	< .001

Note. Null model includes Age, Gender, Nationality

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_0	Regression	1359.585	3	453.195	10.546	< .001
	Residual	15342.015	357	42.975		
	Total	16701.600	360			

Note. Null model includes Age, Gender, Nationality

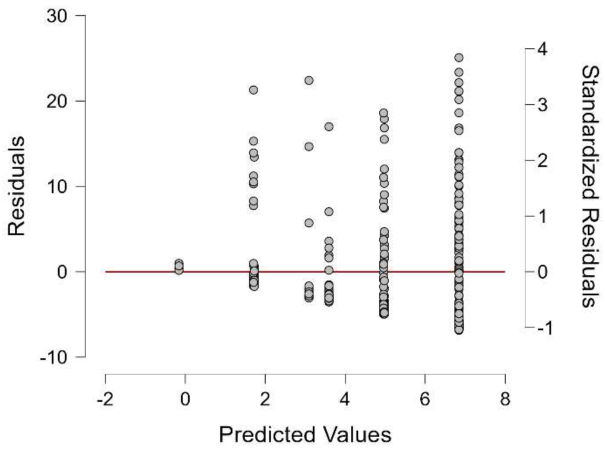
Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p
H_0	(Intercept)	-0.160	1.023		-0.156	0.876
	Age	1.885	0.787	0.122	2.395	0.017
	Gender	1.867	0.795	0.119	2.348	0.019
	Nationality	3.252	0.775	0.214	4.195	< .001

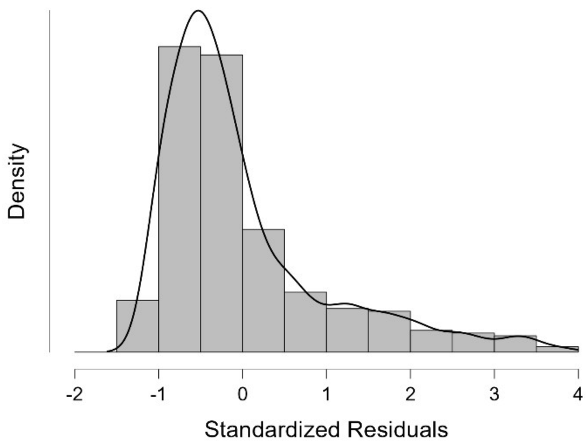
Coefficients Covariance Matrix

Model		Age	Gender	Nationality
H_0	Age	0.620	0.011	-0.058
	Gender		0.633	-0.025
	Nationality			0.601

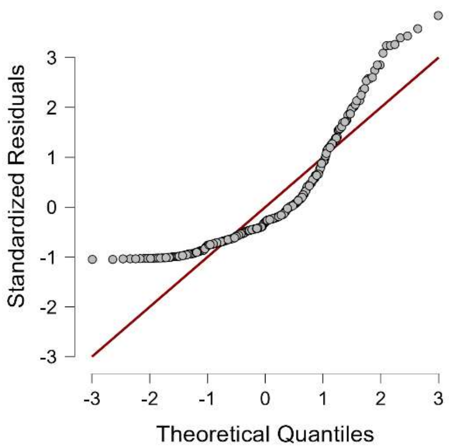
Residuals vs. Predicted



Standardized Residuals Histogram



Q-Q Plot Standardized Residuals



Appendix Z

Hierarchical regression results for the number of hours spent on TikTok in the past week in total: Block 2 (personality traits)

Hours Total Block 2: Personality traits

Model Summary - App Data Hours Total

										Durbin-Watson		
Model	**R**	**R^2**	**Adjusted R^2**	**RMSE**	**R^2 Change**	**F Change**	**df1**	**df2**	**p**	**Autocorrelation**	**Statistic**	**p**
H_0	0.244	0.059	0.046	6.652	0.059	4.488	5	355	< .001	0.292	1.400	< .001
H_1	0.340	0.115	0.095	6.478	0.056	7.426	3	352	< .001	0.230	1.520	< .001

Note. Null model includes Extraversion, Agreeableness, Conscientiousness, Neuroticism, Openness

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_0	Regression	993.056	5	198.611	4.488	< .001
	Residual	15708.544	355	44.249		
	Total	16701.600	360			
H_1	Regression	1928.078	8	241.010	5.742	< .001
	Residual	14773.522	352	41.970		
	Total	16701.600	360			

Note. Null model includes Extraversion, Agreeableness, Conscientiousness, Neuroticism, Openness

Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p
H_0	(Intercept)	4.998	2.994		1.669	0.096
	Extraversion	0.382	0.192	0.114	1.991	0.047
	Agreeableness	0.344	0.203	0.092	1.697	0.091
	Conscientiousness	-0.447	0.217	-0.108	-2.057	0.040
	Neuroticism	0.445	0.186	0.136	2.399	0.017
	Openness	-0.619	0.204	-0.158	-3.032	0.003
H_1	(Intercept)	2.925	2.977		0.983	0.327

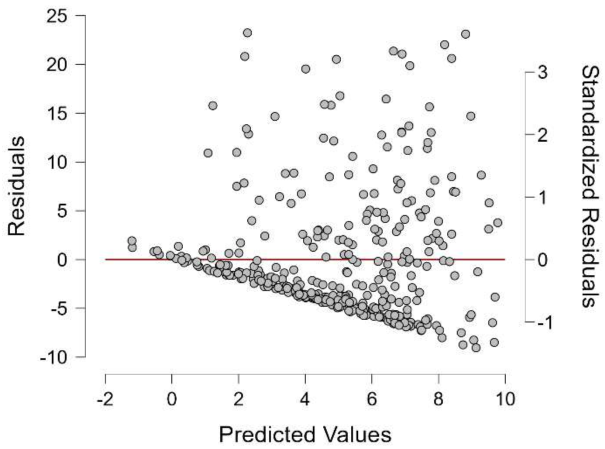
Coefficients

Model	Unstandardized	Standard Error	Standardized	t	p
Age	1.836	0.788	0.119	2.330	0.020
Gender	1.706	0.855	0.109	1.995	0.047
Nationality	2.761	0.795	0.182	3.472	< .001
Extraversion	0.235	0.190	0.070	1.238	0.216
Agreeableness	0.274	0.200	0.074	1.374	0.170
Conscientiousness	-0.496	0.214	-0.120	-2.317	0.021
Neuroticism	0.143	0.199	0.044	0.719	0.472
Openness	-0.456	0.204	-0.117	-2.235	0.026

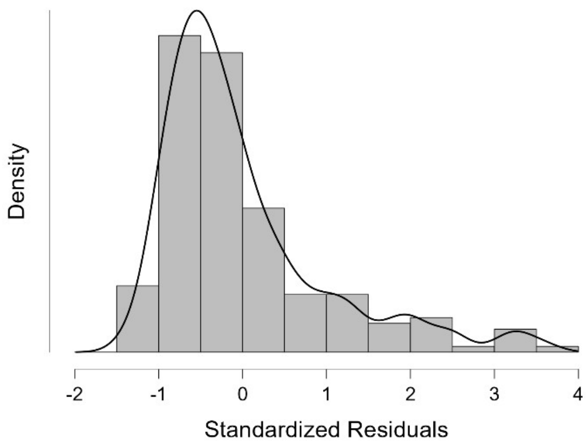
Coefficients Covariance Matrix

Model		Extraversion	Agreeableness	Conscientiousness	Neuroticism	Openness	Age	Gender	Nationality
H_0	Extraversion	0.037	-0.009	-0.003	0.011	-0.004			
	Agreeableness		0.041	-3.283×10^{-4}	0.004	-0.004			
	Conscientiousness			0.047	0.006	-0.002			
	Neuroticism				0.034	-0.004			
	Openness					0.042			
H_1	Extraversion	-0.007	0.009	0.011	-0.016	-0.008	0.621	0.030	-0.057
	Agreeableness		-0.020	-0.024	-0.064	0.015	0.030	0.731	0.018
	Conscientiousness			-0.008	-0.025	0.034	-0.057	0.018	0.632
	Neuroticism				0.013	-0.005	-0.007	-0.009	-0.023
	Openness					-0.005	0.009	-0.020	-0.012
	Age						0.011	-0.024	-0.008
	Gender							-0.064	-0.025
	Nationality								0.034

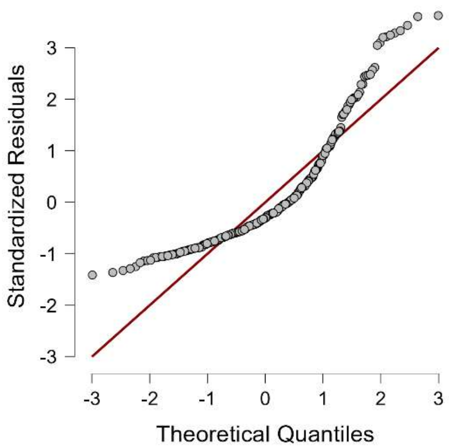
Residuals vs. Predicted



Standardized Residuals Histogram



Q-Q Plot Standardized Residuals



Appendix AA

Hierarchical regression results for the number of hours spent on TikTok in the past week in total: Block 3 (motives for TikTok use)

Model Summary - App Data Hours Total

										Durbin-Watson		
Model	R	R^2	Adjusted R^2	RMSE	R^2 Change	F Change	df1	df2	p	Autocorrelation	Statistic	p
H_0	0.140	0.019	0.008	6.782	0.019	1.769	4	356	0.135	0.331	1.321	< .001
H_1	0.352	0.124	0.094	6.485	0.104	5.180	8	348	< .001	0.249	1.483	< .001

Note. Null model includes Socially rewarding self-presentation, Trendiness, Escapist addiction, Novelty

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_0	Regression	325.457	4	81.364	1.769	0.135
	Residual	16376.144	356	46.000		
	Total	16701.600	360			
H_1	Regression	2067.899	12	172.325	4.098	< .001
	Residual	14633.702	348	42.051		
	Total	16701.600	360			

Note. Null model includes Socially rewarding self-presentation, Trendiness, Escapist addiction, Novelty

Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p
H_0	(Intercept)	0.616	2.309		0.267	0.790
	Socially rewarding self-presentation	0.039	0.050	0.046	0.786	0.432
	Trendiness	0.072	0.168	0.029	0.428	0.669
	Escapist addiction	0.235	0.119	0.117	1.976	0.049
	Novelty	-0.451	0.416	-0.063	-1.084	0.279
H_1	(Intercept)	0.151	3.527		0.043	0.966
	Age	1.899	0.815	0.123	2.331	0.020

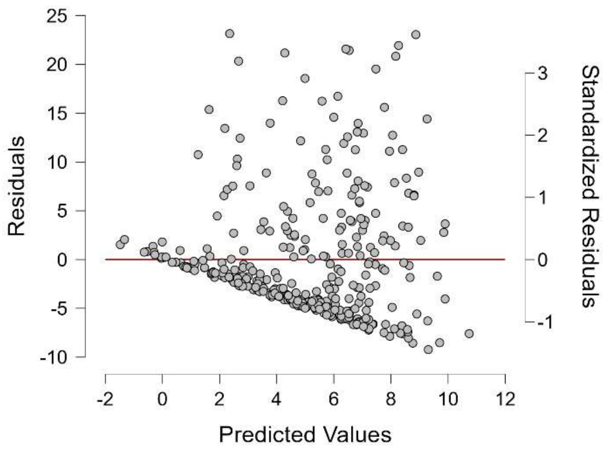
Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p
	Gender	1.549	0.871	0.099	1.780	0.076
	Nationality	2.841	0.805	0.187	3.529	< .001
	Extraversion	0.202	0.191	0.060	1.061	0.290
	Agreeableness	0.241	0.202	0.065	1.192	0.234
	Conscientiousness	-0.513	0.218	-0.124	-2.350	0.019
	Neuroticism	0.118	0.202	0.036	0.585	0.559
	Openness	-0.433	0.206	-0.111	-2.106	0.036
	Socially rewarding self-presentation	0.056	0.049	0.066	1.145	0.253
	Trendiness	0.012	0.162	0.005	0.075	0.940
	Escapist addiction	0.095	0.121	0.047	0.782	0.435
	Novelty	0.085	0.414	0.012	0.205	0.838

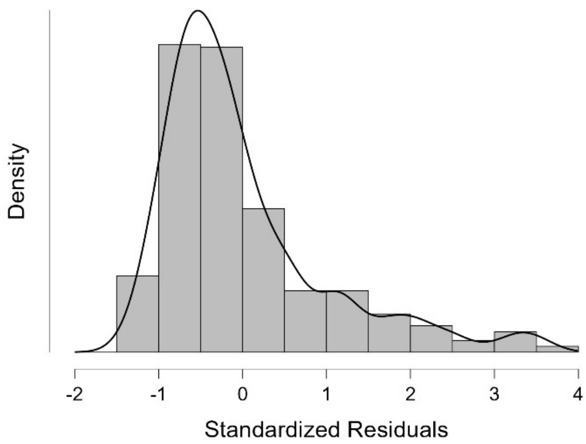
Coefficients Covariance Matrix

Model		Socially rewarding self-presentation	Trendiness	Escapist addiction	Novelty	Age	Gender	Nationality	Extraversion	Agreeableness	Conscientiousness	Neuroticism	Openness
H_0	Socially rewarding self-presentation	0.002	-0.004	4.892×10^{-4}	-3.914×10^{-4}								
	Trendiness		0.028	-0.007	-0.019								
	Escapist addiction			0.014	-0.007								
	Novelty				0.173								
H_1	Socially rewarding self-presentation	0.006	-0.006	-0.016	0.049	0.664	0.050	-0.052	-0.009	0.006	0.003	-0.013	-0.010
	Trendiness		-0.002	-0.017	-0.001	0.050	0.758	0.008	-0.008	-0.020	-0.027	-0.060	0.014
	Escapist addiction			0.005	0.043	-0.052	0.008	0.648	-0.023	-0.014	-0.009	-0.028	0.033
	Novelty				-0.001	-0.009	-0.008	-0.023	0.036	-0.007	-0.002	0.013	-0.005
	Age					0.006	-0.020	-0.014	-0.007	0.041	0.002	0.006	-0.005
	Gender						-0.027	-0.009	-0.002	0.002	0.048	0.007	-0.002
	Nationality							-0.028	0.013	0.006	0.007	0.041	-0.006
	Extraversion								-0.005	-0.005	-0.002	-0.006	0.042
	Agreeableness									-4.337×10^{-4}	-7.986×10^{-4}	2.566×10^{-4}	5.462×10^{-4}
	Conscientiousness										-5.194×10^{-4}	8.710×10^{-4}	-5.769×10^{-5}
	Neuroticism											-0.003	0.002
	Openness												-0.007

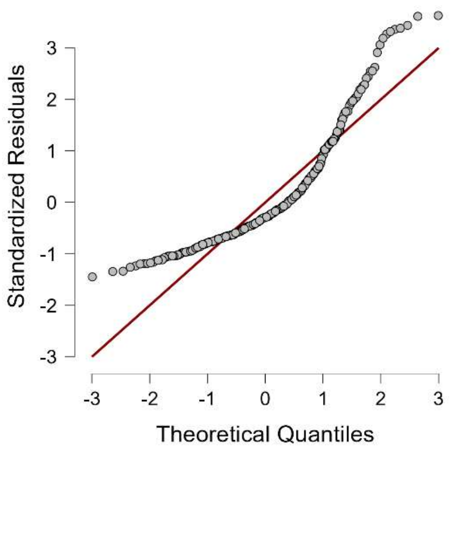
Residuals vs. Predicted



Standardized Residuals Histogram



Q-Q Plot Standardized Residuals



Appendix AB

Hierarchical regression results for the number of times users opened TikTok in the past week during day-time (6am-10pm): Block 1 (demographic factors)

Model Summary - App Data Times Opened Day

										Durbin-Watson		
Model	**R**	**R^2**	**Adjusted R^2**	**RMSE**	**R^2 Change**	**F Change**	**df1**	**df2**	**p**	**Autocorrelation**	**Statistic**	**p**
H_0	0.242	0.058	0.050	70.649	0.058	7.382	3	357	< .001	-0.026	2.051	0.668

Note. Null model includes Age, Gender, Nationality

ANOVA

Model		**Sum of Squares**	**df**	**Mean Square**	**F**	**p**
H_0	Regression	110533.438	3	36844.479	7.382	< .001
	Residual	$1.782 \times 10^{+6}$	357	4991.276		
	Total	$1.892 \times 10^{+6}$	360			

Note. Null model includes Age, Gender, Nationality

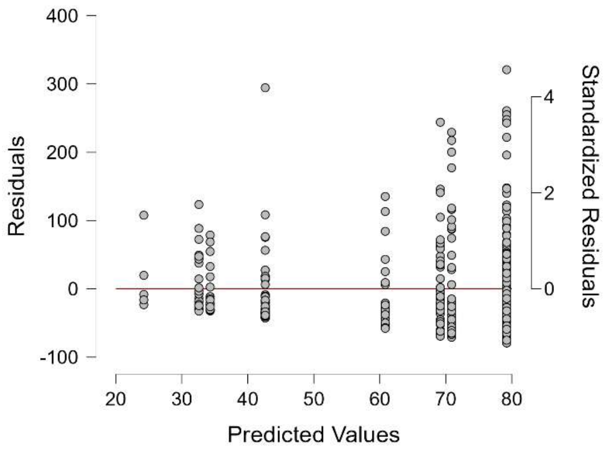
Coefficients

Model		**Unstandardized**	**Standard Error**	**Standardized**	**t**	**p**
H_0	(Intercept)	24.242	11.024		2.199	0.029
	Age	36.583	8.483	0.222	4.313	< .001
	Gender	8.344	8.572	0.050	0.973	0.331
	Nationality	10.053	8.353	0.062	1.204	0.230

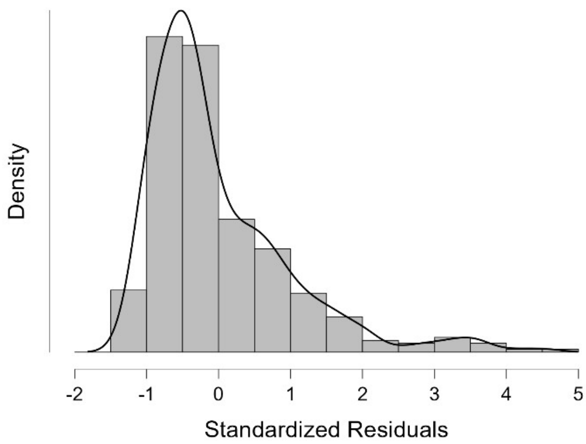
Coefficients Covariance Matrix

Model		**Age**	**Gender**	**Nationality**
H_0	Age	71.961	1.277	-6.702
	Gender		73.474	-2.956
	Nationality			69.770

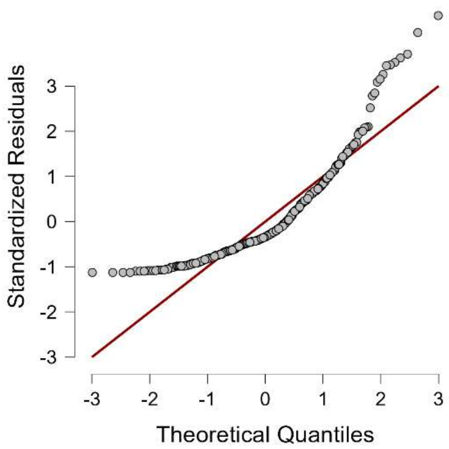
Residuals vs. Predicted



Standardized Residuals Histogram



Q-Q Plot Standardized Residuals



Appendix AC

Hierarchical regression results for the number of times users opened TikTok in the past week during day-time (6am-10pm): Block 2 (personality traits)

Model Summary - App Data Times Opened Day

										Durbin-Watson		
Model	R	R^2	Adjusted R^2	RMSE	R^2 Change	F Change	df1	df2	p	Autocorrelation	Statistic	p
H_0	0.151	0.023	0.009	72.169	0.023	1.668	5	355	0.142	-0.005	2.010	0.932
H_1	0.279	0.078	0.057	70.409	0.055	6.989	3	352	< .001	-0.034	2.067	0.563

Note. Null model includes Extraversion, Agreeableness, Conscientiousness, Neuroticism, Openness

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_0	Regression	43433.501	5	8686.700	1.668	0.142
	Residual	$1.849 \times 10^{+6}$	355	5208.410		
	Total	$1.892 \times 10^{+6}$	360			
H_1	Regression	147384.188	8	18423.024	3.716	< .001
	Residual	$1.745 \times 10^{+6}$	352	4957.485		
	Total	$1.892 \times 10^{+6}$	360			

Note. Null model includes Extraversion, Agreeableness, Conscientiousness, Neuroticism, Openness

Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p
H_0	(Intercept)	105.092	32.486		3.235	0.001
	Extraversion	1.630	2.082	0.046	0.783	0.434
	Agreeableness	0.496	2.200	0.012	0.226	0.822
	Conscientiousness	-3.627	2.358	-0.082	-1.538	0.125
	Neuroticism	1.276	2.014	0.036	0.633	0.527
	Openness	-5.034	2.214	-0.121	-2.273	0.024
H_1	(Intercept)	79.685	32.357		2.463	0.014
	Age	37.188	8.566	0.226	4.341	< .001

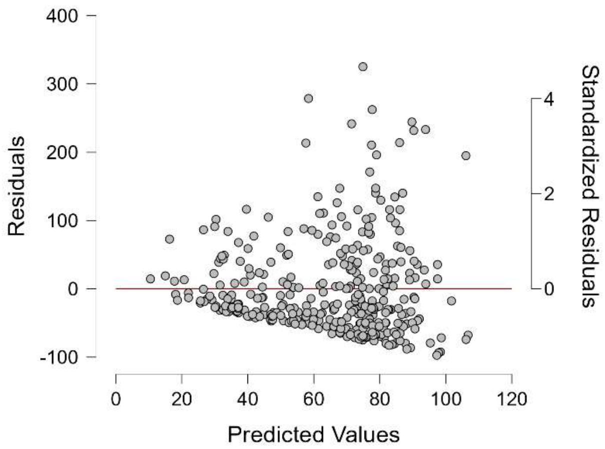
Coefficients

Model	Unstandardized	Standard Error	Standardized	t	p
Gender	9.873	9.293	0.059	1.062	0.289
Nationality	6.881	8.643	0.043	0.796	0.426
Extraversion	0.727	2.061	0.020	0.353	0.724
Agreeableness	0.631	2.172	0.016	0.291	0.772
Conscientiousness	-3.345	2.327	-0.076	-1.437	0.152
Neuroticism	-0.786	2.164	-0.022	-0.363	0.717
Openness	-4.800	2.218	-0.115	-2.164	0.031

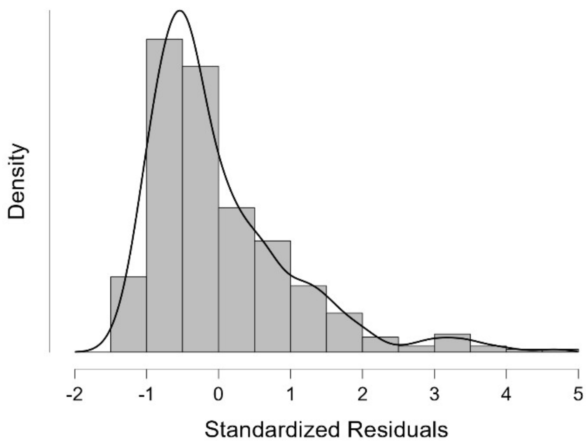
Coefficients Covariance Matrix

Model		Extraversion	Agreeableness	Conscientiousness	Neuroticism	Openness	Age	Gender	Nationality
H_0	Extraversion	4.334	-1.003	-0.391	1.337	-0.445			
	Agreeableness		4.842	-0.039	0.522	-0.489			
	Conscientiousness			5.560	0.666	-0.251			
	Neuroticism				4.058	-0.463			
	Openness					4.904			
H_1	Extraversion	-0.861	1.066	1.274	-1.892	-0.919	73.378	3.508	-6.677
	Agreeableness		-2.394	-2.796	-7.619	1.821	3.508	86.351	2.079
	Conscientiousness			-0.898	-2.954	4.002	-6.677	2.079	74.694
	Neuroticism				1.493	-0.578	-0.861	-1.076	-2.678
	Openness					-0.600	1.066	-2.394	-1.463
	Age						1.274	-2.796	-0.898
	Gender							-7.619	-2.954
	Nationality								4.002

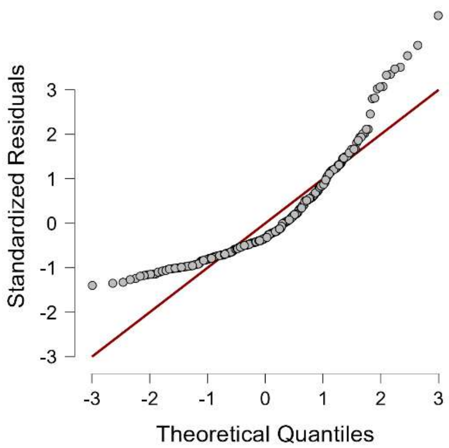
Residuals vs. Predicted



Standardized Residuals Histogram



Q-Q Plot Standardized Residuals



Appendix AD

Hierarchical regression results for the number of times users opened TikTok in the past week during day-time (6am-10pm): Block 3 (motives for TikTok use)

Model Summary - App Data Times Opened Day

										Durbin-Watson		
Model	R	R^2	Adjusted R^2	RMSE	R^2 Change	F Change	df1	df2	p	Autocorrelation	Statistic	p
H_0	0.304	0.092	0.082	69.456	0.092	9.071	4	356	< .001	-0.007	2.014	0.902
H_1	0.386	0.149	0.120	68.023	0.057	2.895	8	348	0.004	-0.042	2.084	0.462

Note. Null model includes Socially rewarding self-presentation, Trendiness, Escapist addiction, Novelty

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_0	Regression	175042.897	4	43760.724	9.071	< .001
	Residual	$1.717\times10^{+6}$	356	4824.090		
	Total	$1.892\times10^{+6}$	360			
H_1	Regression	282192.502	12	23516.042	5.082	< .001
	Residual	$1.610\times10^{+6}$	348	4627.087		
	Total	$1.892\times10^{+6}$	360			

Note. Null model includes Socially rewarding self-presentation, Trendiness, Escapist addiction, Novelty

Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p
H_0	(Intercept)	-45.589	23.648		-1.928	0.055
	Socially rewarding self-presentation	-0.283	0.510	-0.032	-0.555	0.579
	Trendiness	0.110	1.722	0.004	0.064	0.949
	Escapist addiction	6.684	1.218	0.313	5.488	< .001
	Novelty	-2.566	4.259	-0.033	-0.603	0.547
H_1	(Intercept)	-20.111	36.995		-0.544	0.587
	Age	31.642	8.549	0.192	3.701	< .001

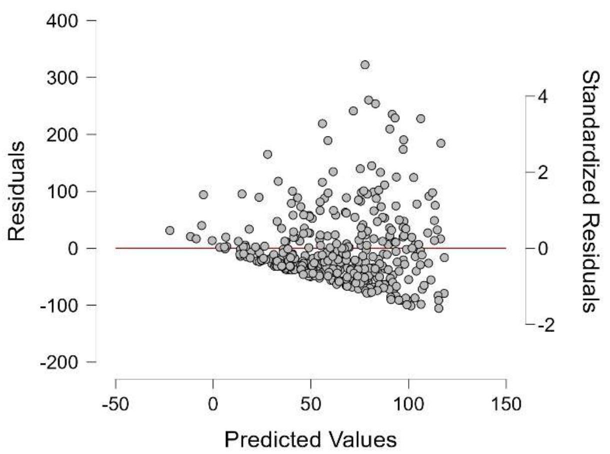
Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p
	Gender	1.016	9.132	0.006	0.111	0.911
	Nationality	10.864	8.444	0.067	1.287	0.199
	Extraversion	0.343	2.002	0.010	0.171	0.864
	Agreeableness	0.316	2.119	0.008	0.149	0.882
	Conscientiousness	-2.526	2.289	-0.057	-1.103	0.271
	Neuroticism	-2.409	2.114	-0.069	-1.140	0.255
	Openness	-4.282	2.158	-0.103	-1.984	0.048
	Socially rewarding self-presentation	-0.084	0.512	-0.009	-0.165	0.869
	Trendiness	-0.351	1.698	-0.013	-0.207	0.836
	Escapist addiction	5.961	1.272	0.279	4.684	< .001
	Novelty	2.312	4.342	0.030	0.533	0.595

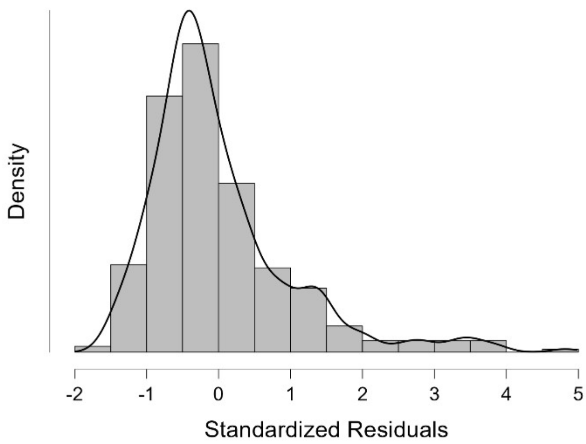
Coefficients Covariance Matrix

Model		Socially rewarding self-presentation	Trendiness	Escapist addiction	Novelty	Age	Gender	Nationality	Extraversion	Agreeableness	Conscientiousness	Neuroticism	Openness
H_0	Socially rewarding self-presentation	0.260	-0.369	0.051	-0.041								
	Trendiness		2.966	-0.772	-1.981								
	Escapist addiction			1.483	-0.765								
	Novelty				18.138								
H_1	Socially rewarding self-presentation	0.646	-0.613	-1.776	5.399	73.077	5.467	-5.731	-0.984	0.618	0.317	-1.423	-1.072
	Trendiness		-0.195	-1.820	-0.138	5.467	83.389	0.847	-0.923	-2.179	-2.940	-6.611	1.552
	Escapist addiction			0.508	4.711	-5.731	0.847	71.305	-2.552	-1.546	-1.019	-3.027	3.599
	Novelty				-0.110	-0.984	-0.923	-2.552	4.008	-0.779	-0.261	1.401	-0.559
	Age					0.618	-2.179	-1.546	-0.779	4.491	0.171	0.691	-0.546
	Gender						-2.940	-1.019	-0.261	0.171	5.241	0.767	-0.274
	Nationality							-3.027	1.401	0.691	0.767	4.470	-0.699
	Extraversion								-0.559	-0.546	-0.274	-0.699	4.656
	Agreeableness									-0.048	-0.088	0.028	0.060
	Conscientiousness										-0.057	0.096	-0.006
	Neuroticism											-0.348	0.180
	Openness												-0.804

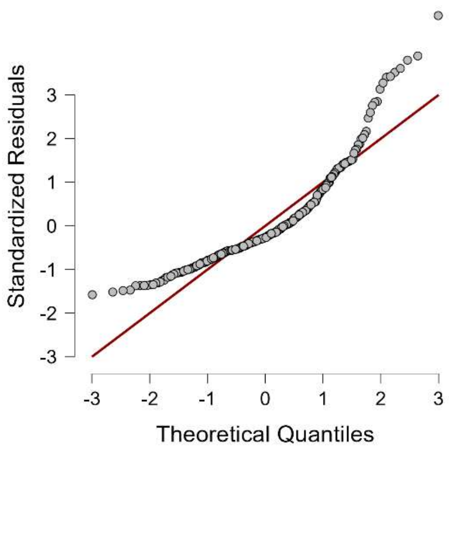
Residuals vs. Predicted



Standardized Residuals Histogram



Q-Q Plot Standardized Residuals



Appendix AE

Hierarchical regression results for the number of times users opened TikTok in the past week during night-time (10pm-6am): Block 1 (demographic factors)

Model Summary - App Data Times Opened Night

										Durbin-Watson		
Model	R	R^2	Adjusted R^2	RMSE	R^2 Change	F Change	df1	df2	p	Autocorrelation	Statistic	p
H_0	0.216	0.047	0.039	34.569	0.047	5.848	3	357	< .001	-0.014	2.026	0.848

Note. Null model includes Age, Gender, Nationality

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_0	Regression	20966.735	3	6988.912	5.848	< .001
	Residual	426625.265	357	1195.029		
	Total	447592.000	360			

Note. Null model includes Age, Gender, Nationality

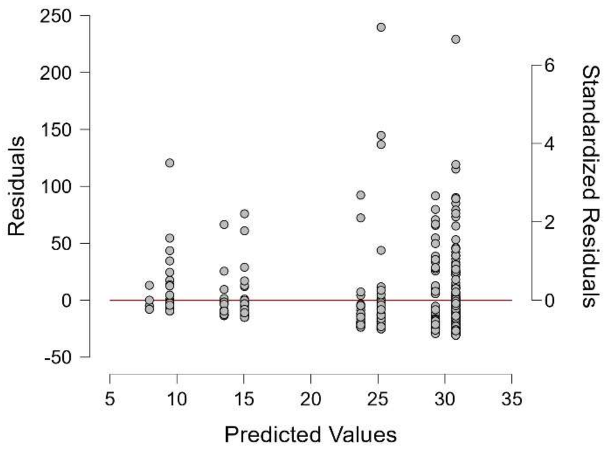
Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p
H_0	(Intercept)	7.957	5.394		1.475	0.141
	Age	15.760	4.151	0.197	3.797	< .001
	Gender	1.519	4.194	0.019	0.362	0.717
	Nationality	5.575	4.087	0.071	1.364	0.173

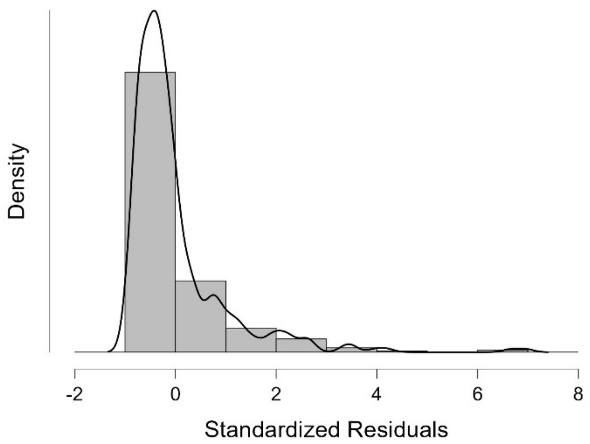
Coefficients Covariance Matrix

Model		Age	Gender	Nationality
H_0	Age	17.229	0.306	-1.605
	Gender		17.592	-0.708
	Nationality			16.705

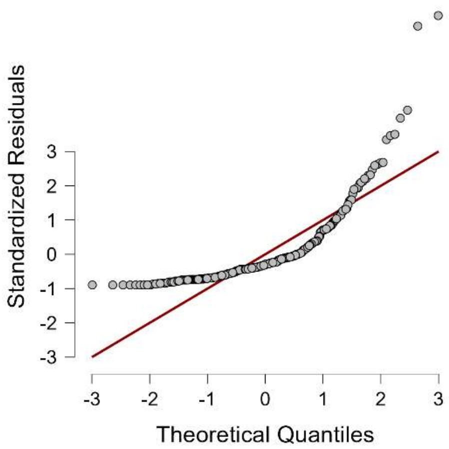
Residuals vs. Predicted



Standardized Residuals Histogram



Q-Q Plot Standardized Residuals



Appendix AF

Hierarchical regression results for the number of times users opened TikTok in the past week during night-time (10pm-6am): Block 2 (personality traits)

Model Summary - App Data Times Opened Night

										Durbin-Watson		
Model	R	R^2	Adjusted R^2	RMSE	R^2 Change	F Change	df1	df2	p	Autocorrelation	Statistic	p
H_0	0.146	0.021	0.008	35.126	0.021	1.554	5	355	0.172	0.016	1.968	0.753
H_1	0.260	0.068	0.046	34.432	0.046	5.813	3	352	< .001	-0.021	2.039	0.754

Note. Null model includes Extraversion, Agreeableness, Conscientiousness, Neuroticism, Openness

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_0	Regression	9588.711	5	1917.742	1.554	0.172
	Residual	438003.289	355	1233.812		
	Total	447592.000	360			
H_1	Regression	30263.312	8	3782.914	3.191	0.002
	Residual	417328.688	352	1185.593		
	Total	447592.000	360			

Note. Null model includes Extraversion, Agreeableness, Conscientiousness, Neuroticism, Openness

Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p
H_0	(Intercept)	41.714	15.811		2.638	0.009
	Extraversion	-0.321	1.013	-0.019	-0.317	0.751
	Agreeableness	1.537	1.071	0.080	1.435	0.152
	Conscientiousness	-2.099	1.148	-0.098	-1.829	0.068
	Neuroticism	0.166	0.980	0.010	0.169	0.866
	Openness	-1.652	1.078	-0.082	-1.532	0.126
H_1	(Intercept)	29.449	15.823		1.861	0.064
	Age	16.254	4.189	0.203	3.880	< .001

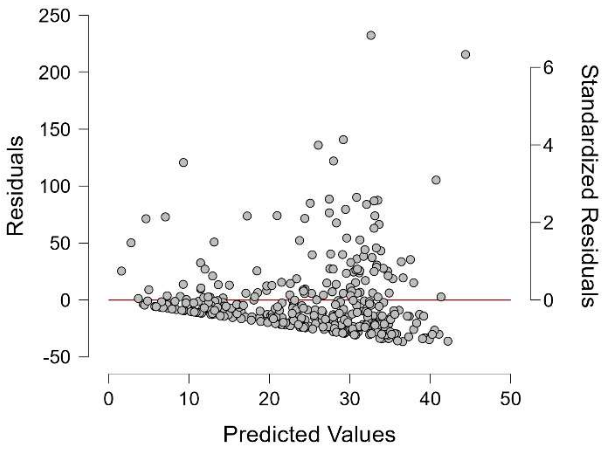
Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p
	Gender	2.295	4.544	0.028	0.505	0.614
	Nationality	4.905	4.226	0.062	1.161	0.247
	Extraversion	-0.764	1.008	-0.044	-0.758	0.449
	Agreeableness	1.619	1.062	0.084	1.525	0.128
	Conscientiousness	-1.927	1.138	-0.090	-1.693	0.091
	Neuroticism	-0.635	1.058	-0.037	-0.600	0.549
	Openness	-1.491	1.085	-0.074	-1.374	0.170

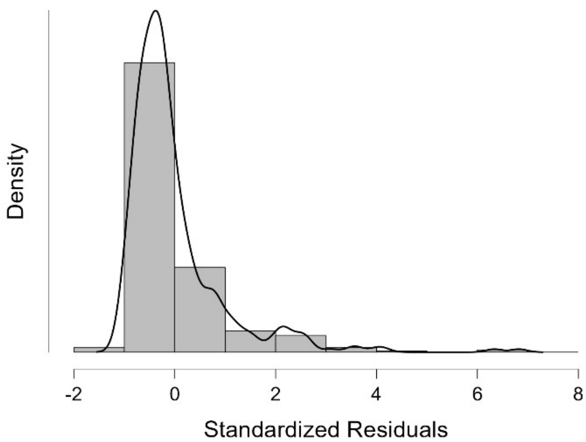
Coefficients Covariance Matrix

Model		Extraversion	Agreeableness	Conscientiousness	Neuroticism	Openness	Age	Gender	Nationality
H_0	Extraversion	1.027	-0.238	-0.093	0.317	-0.105			
	Agreeableness		1.147	-0.009	0.124	-0.116			
	Conscientiousness			1.317	0.158	-0.059			
	Neuroticism				0.961	-0.110			
	Openness					1.162			
H_1	Extraversion	-0.206	0.255	0.305	-0.452	-0.220	17.549	0.839	-1.597
	Agreeableness		-0.573	-0.669	-1.822	0.436	0.839	20.651	0.497
	Conscientiousness			-0.215	-0.707	0.957	-1.597	0.497	17.863
	Neuroticism				0.357	-0.138	-0.206	-0.257	-0.641
	Openness					-0.143	0.255	-0.573	-0.350
	Age						0.305	-0.669	-0.215
	Gender							-1.822	-0.707
	Nationality								0.957

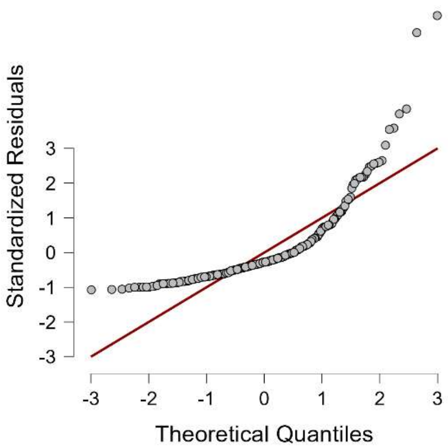
Residuals vs. Predicted



Standardized Residuals Histogram



Q-Q Plot Standardized Residuals



Appendix AG

Hierarchical regression results for the number of times users opened TikTok in the past week during night-time (10pm-6am): Block 3 (motives for TikTok use)

Model Summary - App Data Times Opened Night

										Durbin-Watson		
Model	R	R^2	Adjusted R^2	RMSE	R^2 Change	F Change	df1	df2	p	Autocorrelation	Statistic	p
H_0	0.184	0.034	0.023	34.850	0.034	3.134	4	356	0.015	0.035	1.929	0.494
H_1	0.309	0.096	0.064	34.105	0.062	2.964	8	348	0.003	-0.008	2.015	0.939

Note. Null model includes Socially rewarding self-presentation, Trendiness, Escapist addiction, Novelty

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_0	Regression	15225.269	4	3806.317	3.134	0.015
	Residual	432366.731	356	1214.513		
	Total	447592.000	360			
H_1	Regression	42806.570	12	3567.214	3.067	< .001
	Residual	404785.430	348	1163.177		
	Total	447592.000	360			

Note. Null model includes Socially rewarding self-presentation, Trendiness, Escapist addiction, Novelty

Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p
H_0	(Intercept)	-9.943	11.865		-0.838	0.403
	Socially rewarding self-presentation	0.227	0.256	0.052	0.888	0.375
	Trendiness	0.172	0.864	0.013	0.199	0.842
	Escapist addiction	1.785	0.611	0.172	2.921	0.004
	Novelty	-1.357	2.137	-0.036	-0.635	0.526
H_1	(Intercept)	-0.626	18.549		-0.034	0.973
	Age	16.054	4.286	0.201	3.746	< .001

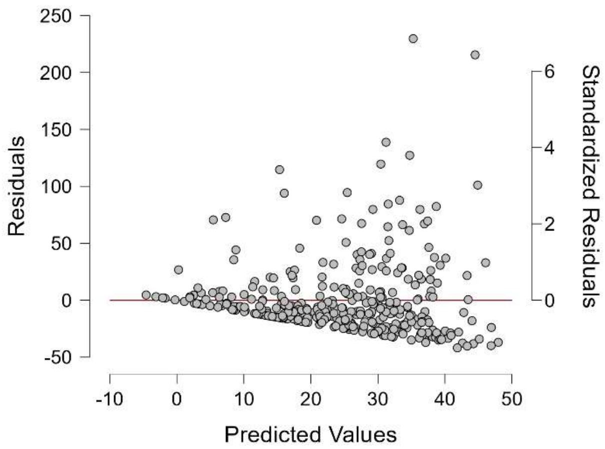
Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p
	Gender	0.215	4.578	0.003	0.047	0.963
	Nationality	5.945	4.234	0.076	1.404	0.161
	Extraversion	-1.022	1.004	-0.059	-1.018	0.309
	Agreeableness	1.362	1.062	0.070	1.282	0.201
	Conscientiousness	-1.944	1.148	-0.091	-1.694	0.091
	Neuroticism	-1.000	1.060	-0.059	-0.943	0.346
	Openness	-1.280	1.082	-0.063	-1.183	0.238
	Socially rewarding self-presentation	0.370	0.256	0.085	1.441	0.150
	Trendiness	-0.048	0.851	-0.004	-0.057	0.955
	Escapist addiction	1.352	0.638	0.130	2.119	0.035
	Novelty	0.970	2.177	0.026	0.446	0.656

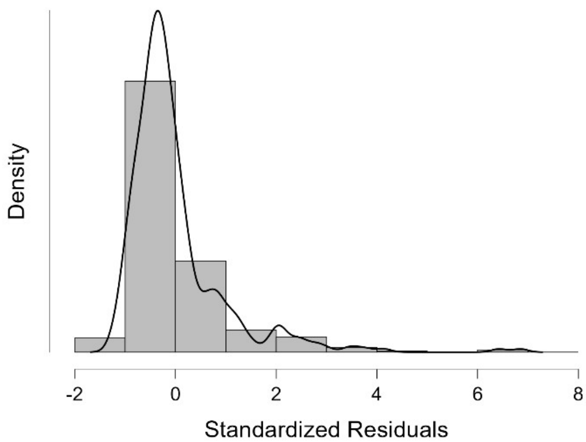
Coefficients Covariance Matrix

Model		Socially rewarding self-presentation	Trendiness	Escapist addiction	Novelty	Age	Gender	Nationality	Extraversion	Agreeableness	Conscientiousness	Neuroticism	Openness
H_0	Socially rewarding self-presentation	0.065	-0.093	0.013	-0.010								
	Trendiness		0.747	-0.194	-0.499								
	Escapist addiction			0.373	-0.192								
	Novelty				4.566								
H_1	Socially rewarding self-presentation	0.163	-0.154	-0.446	1.357	18.370	1.374	-1.441	-0.247	0.155	0.080	-0.358	-0.269
	Trendiness		-0.049	-0.458	-0.035	1.374	20.963	0.213	-0.232	-0.548	-0.739	-1.662	0.390
	Escapist addiction			0.128	1.184	-1.441	0.213	17.925	-0.641	-0.389	-0.256	-0.761	0.905
	Novelty				-0.028	-0.247	-0.232	-0.641	1.007	-0.196	-0.066	0.352	-0.140
	Age					0.155	-0.548	-0.389	-0.196	1.129	0.043	0.174	-0.137
	Gender						-0.739	-0.256	-0.066	0.043	1.317	0.193	-0.069
	Nationality							-0.761	0.352	0.174	0.193	1.124	-0.176
	Extraversion								-0.140	-0.137	-0.069	-0.176	1.171
	Agreeableness									-0.012	-0.022	0.007	0.015
	Conscientiousness										-0.014	0.024	-0.002
	Neuroticism											-0.088	0.045
	Openness												-0.202

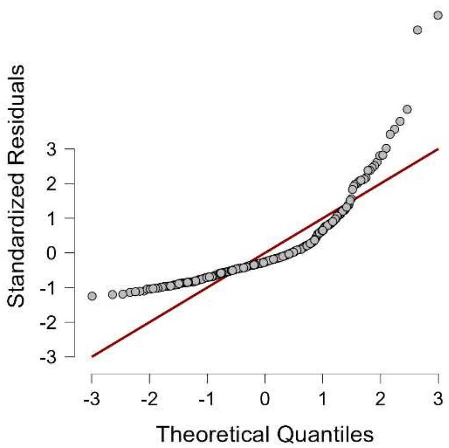
Residuals vs. Predicted



Standardized Residuals Histogram



Q-Q Plot Standardized Residuals



Appendix AH

Hierarchical regression results for the number of times users opened TikTok in the past week in total: Block 1 (demographic factors)

Model Summary - App Data Times Opened Total

										Durbin-Watson		
Model	R	R^2	Adjusted R^2	RMSE	R^2 Change	F Change	df1	df2	p	Autocorrelation	Statistic	p
H_0	0.255	0.065	0.057	95.513	0.065	8.290	3	357	< .001	-0.028	2.056	0.631

Note. Null model includes Age, Gender, Nationality

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_0	Regression	226880.573	3	75626.858	8.290	< .001
	Residual	$3.257\times10^{+6}$	357	9122.791		
	Total	$3.484\times10^{+6}$	360			

Note. Null model includes Age, Gender, Nationality

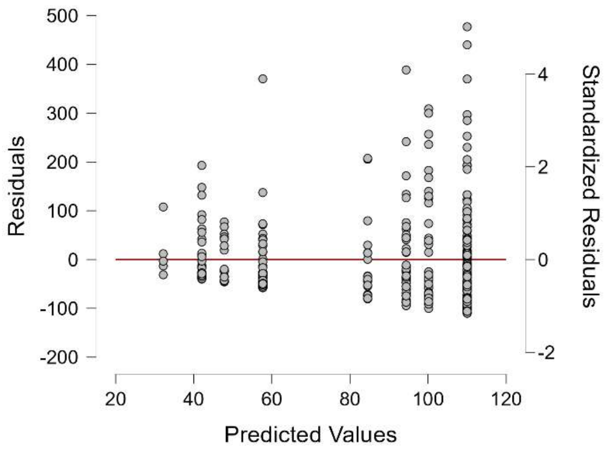
Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p
H_0	(Intercept)	32.199	14.904		2.160	0.031
	Age	52.343	11.469	0.235	4.564	< .001
	Gender	9.863	11.588	0.044	0.851	0.395
	Nationality	15.628	11.293	0.071	1.384	0.167

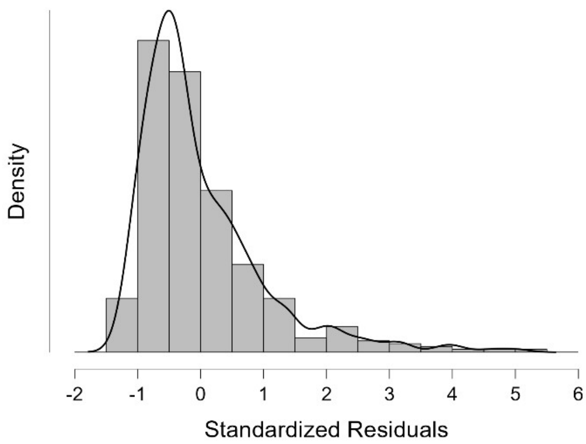
Coefficients Covariance Matrix

Model		Age	Gender	Nationality
H_0	Age	131.527	2.333	-12.250
	Gender		134.293	-5.402
	Nationality			127.522

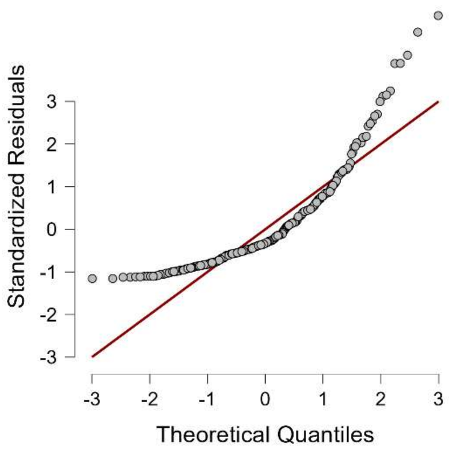
Residuals vs. Predicted



Standardized Residuals Histogram



Q-Q Plot Standardized Residuals



Appendix AI

Hierarchical regression results for the number of times users opened TikTok in the past week in total: Block 2 (personality traits)

Model Summary - App Data Times Opened Total

										Durbin-Watson		
Model	R	R^2	Adjusted R^2	RMSE	R^2 Change	F Change	df1	df2	p	Autocorrelation	Statistic	p
H_0	0.158	0.025	0.011	97.826	0.025	1.806	5	355	0.111	-0.001	2.002	0.991
H_1	0.295	0.087	0.066	95.064	0.062	7.976	3	352	< .001	-0.040	2.079	0.489

Note. Null model includes Extraversion, Agreeableness, Conscientiousness, Neuroticism, Openness

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_0	Regression	86419.350	5	17283.870	1.806	0.111
	Residual	$3.397\times10^{+6}$	355	9569.853		
	Total	$3.484\times10^{+6}$	360			
H_1	Regression	302658.720	8	37832.340	4.186	< .001
	Residual	$3.181\times10^{+6}$	352	9037.098		
	Total	$3.484\times10^{+6}$	360			

Note. Null model includes Extraversion, Agreeableness, Conscientiousness, Neuroticism, Openness

Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p
H_0	(Intercept)	146.806	44.035		3.334	< .001
	Extraversion	1.309	2.822	0.027	0.464	0.643
	Agreeableness	2.034	2.983	0.038	0.682	0.496
	Conscientiousness	-5.726	3.196	-0.096	-1.791	0.074
	Neuroticism	1.442	2.731	0.030	0.528	0.598
	Openness	-6.685	3.002	-0.119	-2.227	0.027
H_1	(Intercept)	109.135	43.686		2.498	0.013
	Age	53.441	11.566	0.240	4.621	< .001

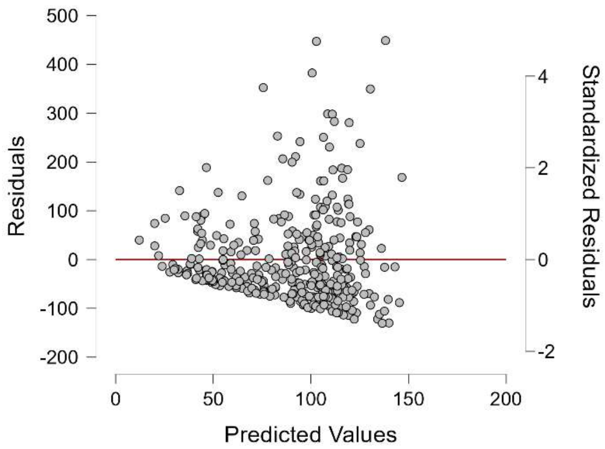
Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p
	Gender	12.167	12.546	0.054	0.970	0.333
	Nationality	11.786	11.669	0.054	1.010	0.313
	Extraversion	-0.037	2.783	-7.571×10^{-4}	-0.013	0.990
	Agreeableness	2.250	2.932	0.042	0.767	0.443
	Conscientiousness	-5.272	3.142	-0.088	-1.678	0.094
	Neuroticism	-1.421	2.922	-0.030	-0.486	0.627
	Openness	-6.291	2.995	-0.112	-2.100	0.036

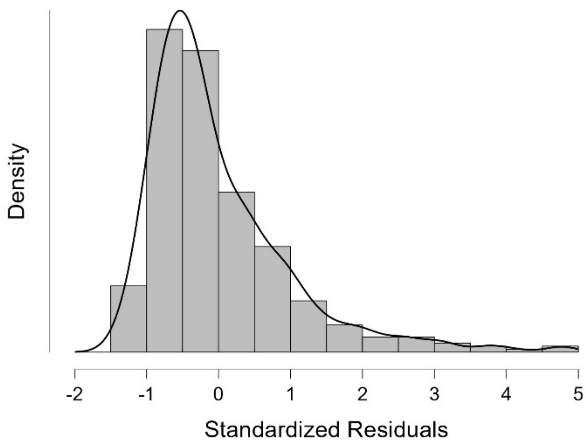
Coefficients Covariance Matrix

Model		Extraversion	Agreeableness	Conscientiousness	Neuroticism	Openness	Age	Gender	Nationality
H_0	Extraversion	7.963	-1.843	-0.718	2.457	-0.818			
	Agreeableness		8.896	-0.071	0.960	-0.899			
	Conscientiousness			10.217	1.225	-0.461			
	Neuroticism				7.456	-0.850			
	Openness					9.010			
H_1	Extraversion	-1.569	1.944	2.322	-3.448	-1.676	133.762	6.395	-12.171
	Agreeableness		-4.365	-5.098	-13.888	3.320	6.395	157.411	3.791
	Conscientiousness			-1.638	-5.385	7.296	-12.171	3.791	136.161
	Neuroticism				2.721	-1.053	-1.569	-1.961	-4.882
	Openness					-1.094	1.944	-4.365	-2.667
	Age						2.322	-5.098	-1.638
	Gender							-13.888	-5.385
	Nationality								7.296

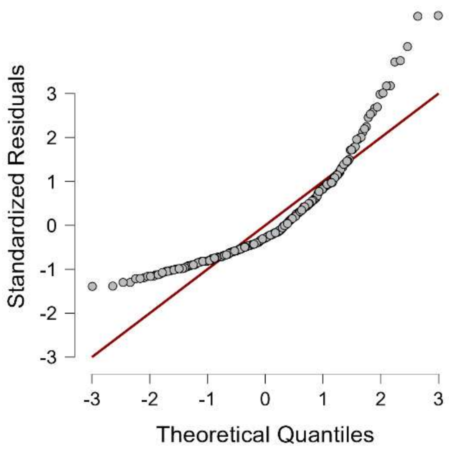
Residuals vs. Predicted



Standardized Residuals Histogram



Q-Q Plot Standardized Residuals



Appendix AJ

Hierarchical regression results for the number of times users opened TikTok in the past week in total: Block 3 (motives for TikTok use)

Model Summary - App Data Times Opened Total

										Durbin-Watson		
Model	R	R^2	Adjusted R^2	RMSE	R^2 Change	F Change	df1	df2	p	Autocorrelation	Statistic	p
H_0	0.286	0.082	0.072	94.789	0.082	7.932	4	356	< .001	0.011	1.978	0.826
H_1	0.386	0.149	0.120	92.286	0.067	3.447	8	348	< .001	-0.035	2.070	0.548

Note. Null model includes Socially rewarding self-presentation, Trendiness, Escapist addiction, Novelty

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_0	Regression	285078.660	4	71269.665	7.932	< .001
	Residual	$3.199\times10^{+6}$	356	8984.939		
	Total	$3.484\times10^{+6}$	360			
H_1	Regression	519922.062	12	43326.839	5.087	< .001
	Residual	$2.964\times10^{+6}$	348	8516.652		
	Total	$3.484\times10^{+6}$	360			

Note. Null model includes Socially rewarding self-presentation, Trendiness, Escapist addiction, Novelty

Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p
H_0	(Intercept)	-55.532	32.273		-1.721	0.086
	Socially rewarding self-presentation	-0.056	0.696	-0.005	-0.080	0.936
	Trendiness	0.282	2.350	0.008	0.120	0.905
	Escapist addiction	8.469	1.662	0.292	5.095	< .001
	Novelty	-3.924	5.812	-0.038	-0.675	0.500
H_1	(Intercept)	-20.738	50.191		-0.413	0.680
	Age	47.696	11.598	0.214	4.113	< .001

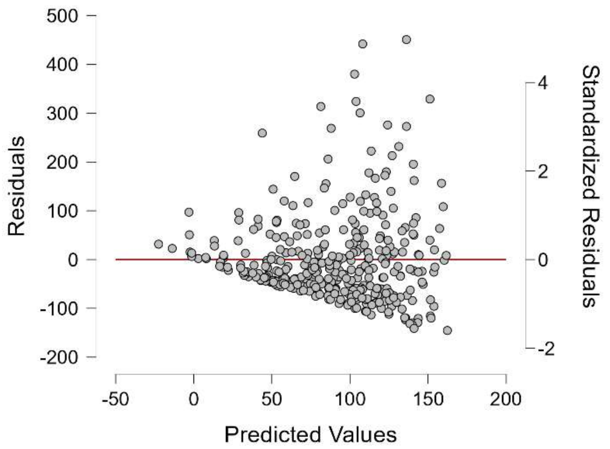
Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p
	Gender	1.230	12.389	0.005	0.099	0.921
	Nationality	16.809	11.456	0.077	1.467	0.143
	Extraversion	-0.678	2.716	-0.014	-0.250	0.803
	Agreeableness	1.678	2.875	0.031	0.584	0.560
	Conscientiousness	-4.470	3.106	-0.075	-1.439	0.151
	Neuroticism	-3.409	2.868	-0.072	-1.189	0.235
	Openness	-5.562	2.928	-0.099	-1.900	0.058
	Socially rewarding self-presentation	0.285	0.694	0.023	0.411	0.681
	Trendiness	-0.400	2.303	-0.011	-0.174	0.862
	Escapist addiction	7.312	1.726	0.252	4.236	< .001
	Novelty	3.282	5.891	0.032	0.557	0.578

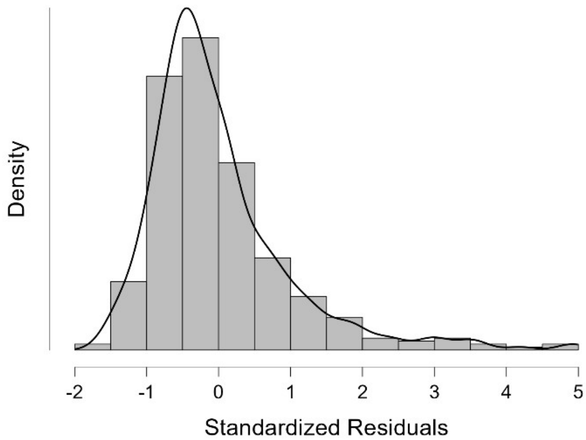
Coefficients Covariance Matrix

Model		Socially rewarding self-presentation	Trendiness	Escapist addiction	Novelty	Age	Gender	Nationality	Extraversion	Agreeableness	Conscientiousness	Neuroticism	Openness
H_0	Socially rewarding self-presentation	0.484	-0.687	0.096	-0.076								
	Trendiness		5.525	-1.438	-3.689								
	Escapist addiction			2.763	-1.424								
	Novelty				33.782								
H_1	Socially rewarding self-presentation	1.190	-1.129	-3.269	9.938	134.506	10.063	-10.548	-1.810	1.137	0.584	-2.619	-1.973
	Trendiness		-0.359	-3.351	-0.253	10.063	153.486	1.560	-1.699	-4.010	-5.411	-12.168	2.857
	Escapist addiction			0.936	8.671	-10.548	1.560	131.244	-4.697	-2.846	-1.875	-5.571	6.625
	Novelty				-0.203	-1.810	-1.699	-4.697	7.376	-1.435	-0.480	2.578	-1.028
	Age					1.137	-4.010	-2.846	-1.435	8.265	0.314	1.272	-1.004
	Gender						-5.411	-1.875	-0.480	0.314	9.646	1.412	-0.504
	Nationality							-5.571	2.578	1.272	1.412	8.227	-1.286
	Extraversion								-1.028	-1.004	-0.504	-1.286	8.570
	Agreeableness									-0.088	-0.162	0.052	0.111
	Conscientiousness										-0.105	0.176	-0.012
	Neuroticism											-0.641	0.332
	Openness												-1.480

Residuals vs. Predicted



Standardized Residuals Histogram



Q-Q Plot Standardized Residuals