7-8-2023

TikTok Use Motivators: A Latent Profile Analysis of TikTok Use Motives

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Completed Research Paper

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Abstract

Prior social media research has identified a range of motives within a classic framework of use and gratification to answer why people use social media. To date, most work has used a variable-centered approach to investigate how TikTok use motives that are quantified with a composite score to influence outcomes. By comparison with prior work, this current study conducted 2 studies (Study 1: full-time employee; Study 2: college student; Ntotal = 680) that investigated TikTok use motives or gratifications following a person-centered approach. We conducted latent profile analysis and identified four profiles of TikTok use motives: deep motivators, lone motivators, mood-elevating motivators, and slight motivators. We also found that these motivator profiles differentially predicted individual outcomes (TikTok addiction, labile self-esteem, subjective well-being, and engagement). Our findings contribute to the TikTok use literature by exploring how TikTok use motives combine and develop different motivator profiles.

Keywords: Social media use, TikTok, motive, latent profile analysis, use and gratification theory

An Overview of the Current Research

TikTok, known as an international social media application (SMA), has taken the world by storm. As opposed to the other SMAs such as Facebook, Instagram, and WhatsApp, TikTok is a short-form video mobile-based application that allows users to create videos lasting 15 seconds to 10 minutes (Barta et al. 2023; Hutchinson 2022) and then share them with the wider TikTok community. The shared videos from TikTok usually cover a variety of content categories including dance, jokes, pranks, tricks, and entertainment (Bailey 2020). From the TikTok statistics (Doyle 2022; Frederick 2022), TikTok is available in 154 countries around the globe, has over 1 billion monthly active users, and has become the most downloaded app worldwide in the first quarter of 2022, beating its competitors such as Facebook, YouTube, and Instagram. The engagement on TikTok is so astonishing that users spend 26 hours per month browsing their TikTok pages (Doyle 2022). Taken together, a basic question is why users gravitate to TikTok with so great dedication.

To date, the use and gratification theory (U&G) is one of the most common approaches to examine how and why social media users seek out specific media and applications (e.g., Katz et al. 1973; Krause et al. 2014; Lonsdale and North 2011; McQuail et al. 1972; Sundar and Limperos 2013; Whiting and Williams 2013). According to this U&G theory, people gravitate to social media to satisfy their psychological needs including surveillance, personal identity, social interaction, and diversion (McQuail et al. 1972); thus, they are not passive receipts. This theory is a well-established framework to explain users' motives for social media use.

To do this, prior work usually asks people to report the reasons why they use specific media and to investigate the relationships of social media use with antecedents and consequences (Bossen and Kottasz 2020; Falgoust et al. 2022; Orchard 2019; Whiting and Williams 2013). This kind of research reflects a variable-centered approach (Howard and Hoffman 2018) in which scholars explain the specific and independent associations of a composite score of social media use motives with other variables. This approach assumes that individuals from a sample belong to a homogeneous group, wherein predictors influence outcomes similarly across groups (Laursen and Hoff 2006). However, this variable-centered approach does not explain people's use of social media to meet different profiles or patterns of psychological needs. These ideas suggest that people's psychological needs or motives for social media use are not treated equally, and their needs will be presented in different configurations. In doing so, a person-centered approach (Howard and Hoffman 2018) is necessary to explore distinct subpopulations of social media use that configure different motives. This approach is appropriate to categorize individuals into subpopulations based on the motives of TikTok use and to investigate the relations of these subpopulations with relevant outcomes in the current study.

In consideration of the unexplored area of the TikTok use research, our study makes the following contributions. First, we used the latent profile analysis (e.g., Muthén 2002; Spurk et al. 2020) to investigate the potential profiles of TikTok use motives. Following the recommended procedure by Wang and Hanges (2011, we initially explored the profiles of TikTok use motives from a Prolific sample (Study 1) and confirmed the structure with a sample of college students (Study 2). The use of the person-centered analysis makes us identify distinct motivational profiles of TikTok use within the U&G framework. Second, we investigated the differential relations of these profiles with outcome variables (e.g., subjective well-being, TikTok addiction, labile self-esteem, study/work engagement) that are criterion-related factors in the social media use literature (Gerson et al. 2016; Griffiths et al. 2014). Taken together, we have advanced the social media use literature by providing insights into the configurational patterns of distinct motives of TikTok use and their relations with individual outcomes.

Literature review

A Review of Variable-Centered Research on TikTok Use Motives

TikTok, a social media application that originated in China, has achieved unprecedented popularity and success around the world (Montag et al. 2021). This phenomenal popularity has caught scholars' attention to exploring why people use TikTok so enthusiastically. This question can be mainly answered by various theories including U&G theory, social impact theory, and self-determination theory (Montag et al. 2021). Thereinto, U&G theory is one of the most used theories which can investigate the motives of TikTok use (e.g., Bossen and Kottasz 2020; Hossain 2019; Meng and Leung 2021; Orchard 2019; Sundar and Limperos 2013; Whiting and Williams 2013). The basic assumption of this theory is that social media use is goal-oriented, and people use certain media to gratify different psychological needs (Falgoust et al. 2022; Katz et al. 1973; Montag et al. 2021). As far as TikTok use is concerned, the U&G theory is helpful for people to identify a range of needs. In previous research, scholars have confirmed distinct motives for TikTok use. For example, the findings of Scherr and Wang (2021 revealed four motives to explain why people use TikTok with a sample of Chinese users: trendiness, novelty, escapist addiction, and socially rewarding self-presentation; Falgoust et al. (2022 put the motives into six categories, explaining the reasons people use TikTok for finding social support, increasing social interaction, enjoying entertainment, seeking and sharing information, escaping from daily life, and increasing communication convenience and utility; another research by Meng and Leung (2021 who identified nine motives of TikTok use: entertainment, information seeking, escape, money making, fashion, sociability seeking, modality, navigability, and interactivity. Taken all together, these studies suggested some similar motives, such as escaping from life, entertainment, and information seeking, as well as some specific motives, such as trendiness, novelty, and navigability.

Borrowing from McQuail et al.'s (1972) original model of media gratification and findings of Lonsdale and North's (2011) U&G analysis, this current study focuses on a six-factor framework as the TikTok use motives that can explain why people actively seek out TikTok application. These six motives include surveillance, personal identity, social interaction, diversion, negative mood management, and positive mood management. *Surveillance* involves the need to learn of what's happening around us, indicating people need to know a trending discussion from TikTok; *personal identity* involves a need to know who we are; *social interaction* refers to establishing a need for interaction with others; *diversion* shows a need for recreation, entertainment, and escape from daily life; *negative mood management* involves a need to relieve and manage negative feelings; *positive mood management* includes a need to promote and optimize positive feelings (Katz et al. 1973; Lonsdale and North 2011; McQuail et al. 1972). This media gratification model (McQuail et al. 1972) is so genetic that some motives suggested in previous research are contained in this framework. For example, the need to be an escapist confirmed by Meng and Leung (2021 and Falgoust et al. (2022 is derived from the diversion motive; the need for social interaction and self-expression suggested by Omar and Dequan (2020 echo with the motive of personal relationships and personal identity, respectively.

Given the emphasis on media gratifications and motives as a deep reason for understanding people's social media use, these constructs have been the focus of previous literature. Prior work has typically investigated these media use gratifications at a variable level (e.g., how much one engages in a certain motive) and explored their independent relationships with other variables (e.g., TikTok consuming behaviors, TikTok engagement behaviors, TikTok use; Meng and Leung 2021; Omar and Dequan 2020; Scherr and Wang 2021). They used a variable-centered analysis (e.g., regression) in their research. However, this type of analysis ignores the possibility that these media gratifications may constrain media usage in a configurational form and the fact that people may use TikTok to achieve combined gratification. The variable-centered analysis is a dominant approach in the field of social science, and its purpose is to analyze linear relationships among variables in a population (Howard and Hoffman 2018). However, this approach fails to detect if subgroups defined by the configurational patterns of the relevant variables exist within a given population. Identifying novel subpopulations with different combinations of TikTok use motives could advance TikTok use literature by offering new insights into the need gratifications of TikTok use and clarifying the relations of these subpopulations with individual outcomes.

A Person-Centered Approach to TikTok Use Motives

Previous research has mainly used variable-centered approaches to explore the dimensional structure of TikTok use motives and its relationship with other variables. For example, scholars used factor analysis to confirm the dimensions of TikTok use motives (Scherr and Wang 2021) and conducted regression analysis to test the relationship between TikTok use and outcomes (Bissonette Mink and Szymanski 2022). However, variable-centered approaches assume that variables affect and predict outcomes separately and across individuals, which potentially overlooks the existence of subpopulations that differ in their conjoined responses to TikTok use. Unlike variable-centered approaches, person-centered approaches enable researchers to fully comprehend how different variables affect outcomes conjointly and within individuals. These approaches are used to identify the interrelatedness among variables that are a function of the unobserved heterogeneity of the population (Howard and Hoffman 2018; Wang and Hanges 2011; Woo et al. 2018). The unobserved heterogeneity can manifest specific patterns or profiles of TikTok use motives through which people can be classified into different unobserved subpopulations. Thus, identifying the unobserved subpopulations based on specific profiles of variables is the main difference between the two approaches.

Within the person-centered analytic framework, scholars can confirm the profiles of variables quantitatively or qualitatively (Marsh et al. 2009; Wang and Hanges 2011). Quantitatively distinct profiles represent differences in the overall level of the profiles, whereas qualitatively distinct profiles represent differences in the shape of the profiles. In our study, quantitatively distinct profiles demonstrate that TikTok users may be classified into profiles according to high, medium, and low scores across all motives of TikTok use. In contrast, qualitatively distinct profiles manifest that TikTok users may be classified into a profile that has a high diversion, positive and negative mood management, and low surveillance, personal identity, and social interaction, or a profile that has high surveillance and social interaction and moderate mood management and low personal identity and diversion, or other profiles with different combinations of motives. Person-centered approaches can provide new theoretical insights into TikTok use motives by considering all motives simultaneously and by identifying the unobserved heterogeneity of the population. As such, these insights may be absent in the variable-centered approaches (Marsh et al. 2009; Spurk et al. 2020; Wang and Hanges 2011). Although variable-centered approaches can consider statistical interactions among the multiple motives of TikTok use (e.g., using regression), the interaction term divides individuals into artificial categories that may not exist (Dahling et al. 2017; Morin et al. 2010). As Zyphur (2009 articulated, switching the analytical mindset from conventional multiple regression to LPA can lead to new theoretical insights.

Due to the inductive nature of LPA (Gabriel et al. 2015; Wang and Hanges 2011), we make no hypotheses a priori about the number or shape of the profiles of TikTok use motives. Following the analytic procedure of LPA, we will explore and confirm whether quantitatively or qualitatively distinct profiles of TikTok use motives exist. Thus, we propose a research question about the profile solutions of TikTok use motives.

Research question 1: Are there quantitatively and qualitatively distinct profiles of TikTok use motives and, if so, how are they combined?

Outcomes of Profile Membership

With the existence of motive profiles of TikTok use, we aim to explore the association between profile membership and a subset of outcomes about TikTok users' subjective well-being, labile self-esteem, TikTok addiction, and engagement. These outcomes are so important for TikTok users that they reflect how users feel and behave after fulfilling needs from TikTok. We believe that LPA may offer new insights into how TikTok use motives to influence outcomes. Because LPA takes a different analytical focus from the regression method. The regression method focuses on the relationship among variables, and the relationships operate separately, whereas LPA focuses on the relationships among individuals who are defined by a distinct profile (Zyphur 2009). The relationship among variables is usually assessed by an association between a composite score of conceptual facets and outcomes, assuming there are similar perceptions across facets (Dahling et al. 2017). Conversely, the relationship among individuals is assessed through an association between latent profile membership and outcomes (Dahling et al. 2017; Lanza et al. 2013; Spurk et al. 2020). Such a relationship depends on the unobserved heterogeneity that often manifests specific configurations or patterns of all conceptual facets (Wang and Hanges 2011).

Previous research suggests that social media addiction is on the increase among people globally and is an important issue in the literature on social media use (e.g., Cao et al. 2020; Griffiths et al. 2014; Hou et al. 2019; Marengo et al. 2022). Social media addiction refers to "individuals' psychological condition of dependence on social media use that can be demonstrated through an indulgent paradigm of social media seeking and use behaviors that take place and interfere with other normal activities (Cao et al. 2020, p. 1307)." Scholars propose that people who indulge in social media addiction often suffer some symptoms including withdrawal, salience, relapse, conflict, and reinstatement (Yang et al. 2016), and social media addiction is associated with negative consequences (e.g., social interaction reduction, mental health; Hou et al. 2019; Procházka et al. 2021). In this paper, we highlight TikTok addiction because previous research has revealed that TikTok has the highest predictive value of addiction compared with other social media applications like Facebook, WhatsApp, Twitter, Instagram, and Snapchat (Marengo et al. 2022). However, it is unclear what psychological needs or motives make people indulge themselves in TikTok addiction.

Subjective well-being refers to people's evaluation of happiness and satisfaction with life (Diener et al. 2018). This evaluation reflects the individual response to their quality of life. Prior studies have indicated that social media use is associated with subjective well-being, which has attracted the attention of a large number of social media scholars (e.g., Kim 2017; Lin et al. 2016; Valenzuela et al. 2009; Webster et al. 2021; Wirtz et al. 2021). However, the research findings on such associations have been inconsistent and controversial (Kim 2017; Masciantonio et al. 2021). Gerson et al. (2016 found a positive association between Facebook use and the measure of subjective well-being. In another study, Sagioglou and Greitemeyer (2014 found a negative association between Facebook activity and subjective well-being (e.g., mood deterioration). Masciantonio and her colleagues in a recent study found that TikTok use was not associated with subjective well-being (Masciantonio et al. 2021). They also highlighted that an important reason for these controversial findings may be the heterogeneity of social media use motivations. Hence, exploring unobserved heterogeneity underlying the motives of social media use may help resolve these disagreements.

Labile self-esteem occurs when an individual's self-esteem fluctuates as a result of daily positive or negative experiences (Dykman 1998). Unlike trait self-esteem, labile self-esteem involves daily fluctuation over time in self-cognition and shows a stronger sensitivity to depression; people with labile self-esteem are thought to react to stress more negatively than people with reasonably stable self-esteem (Roberts and Gotlib 1997). Recent research indicates that social media use may be a critical predictor of psychological functioning like self-esteem (Cingel et al. 2022; Miljeteig and von Soest 2022). However, prior studies show a mixed pattern of relationship between social media use and self-esteem (Cingel et al. 2022). Some studies found that TikTok use is negatively associated with self-esteem (Chamsi et al. 2022; Savira et al. 2022), whereas other studies found a positive association (Brougham 2021). Cingel et al. (2022 suggested that the true effect of social media use on self-esteem is person-specific and future work should consider the motives of social media use. In addition, this discrepancy in these findings may be due to a lack of attention to the degree of fluctuation in self-esteem. In this paper, we focus on labile self-esteem due to its ambulatory monitoring effect on individual self-esteem while individuals have different experiences on TikTok.

The emergence of engagement shows the academic and practical attention to individual positive psychological states; engagement is characterized by its physical-energetic, emotional, and cognitive components (Schaufeli 2013). The concept of engagement has gained growing popularity in positive organizational psychology in the past decades. Scholars from many perspectives—individual differences, job resources, leadership, organizational factors, and social media—explore the way how engagement is stimulated at work. Perhaps social media is an emerging factor engaging people in what they do. Recent research has found that work-related communication in social media was positively associated with work engagement (Oksa et al. 2021); another study has shown that non-work social media use predicted low levels of work engagement between persons, however, was linked to higher levels of work engagement 1 hour later (Syrek et al. 2018). In addition, some studies have shifted their focus from work engagement to study engagement and discovered its association with social media use (Gulzar et al. 2022; Thomas et al. 2020). Although scholars have acknowledged the importance of social media use in driving work and study engagement, little is known about the specific relationship pattern between social media use (especially TikTok) and engagement.

In sum, as highlighted by Wang and Hanges (2011, linking profiles to outcomes is a critical benefit of LPA. We explored whether TikTok use motives' profiles predict differentially these outcomes. Thus, we propose the following question:

Research question 2: Do profiles of TikTok use motives differ in levels of (a) TikTok addiction, (b) subjective well-being, (c) labile self-esteem, and (d) engagement?

Study 1

Method

Participants and procedure.

Following ethical approval, we recruited our participants through Prolific, an online data collection platform, and paid participants £0.9 for completing the required questionnaires. In the recruitment advertisement, we set up two qualifications: full-time employees and active TikTok users (use for at least one year). The requirement for full-time employees ensures that subjects value their work and that they are better represented as a group of employees. In addition, our requirement of at least one year of TikTok use aims to screen whether subjects are true TikTok users. Sufficient time of use represents a higher level of interaction between the platform and the user, and therefore this group of users can have a more credible performance on the measure of motivation to use TikTok. We used two attention check questions to screen these two qualifications. Those who met the qualifiations would participate in this study; those who did not meet the qualifiations would withdraw automatically. Before filling out a formal questionnaire, potential participants were presented with an informed consent, including the purpose, requirements, compensation, and the voluntary nature of this study. This formal questionnaire included a set of scales on the motives of TikTok use, TikTok addiction, subjective well-being, labile self-esteem, work engagement, and their demographic information. In the end, due to serious missing values and failure in attention checks found in 31 paticipants (7.9%), we retained three hundred and sixty-three (92.1%) valid participants for subsequent data analysis. Overall, of all samples, 71% were female, and the average age was 29.8 years (*SD* = 6.55). In terms of education, 22.9% of the participants were high school graduates, 57.2% had a bachelor's degree or equivalent, and 19.6% had a master's degree or equivalent. Their average tenure of the current company was 4.72 years (*SD* = 5.75).

Measures

TikTok use motives. We used a twenty-six-item scale to establish participants' motives for TikTok use (Lonsdale and North 2011). Scored on a seven-point Likert scale (0 = not at all important and 7 = extremely important). The scale has six subscales: (1) personal identity (e.g., 'to create an image for myself'); (2) negative mood management (e.g., 'to help get through difficult times'); (3) positive mood management (e.g., 'to be entertained'); (4) diversion (e.g., 'to pass the time'); (5) surveillance (e.g., 'to obtain useful information for daily life'); (6) social interaction (e.g., 'to spend time with friends'). The Cronbach's alpha value for this scale was 0.88.

TikTok addiction. To assess TikTok addiction, we used the short Smartphone Addiction Scale(Kwon et al. 2013). We scored this ten-item scale on a seven-point Likert scale (1 = strongly disagree; 7= strongly agree), with less addictive tendencies corresponding to the lowest score and the greatest addictive tendencies corresponding to the highest score. We also modified the questionnaire slightly to make it more accessible for participants. As an example, where the original item stated, 'I miss planned work due to smartphone use,' we changed it to 'I miss planned work due to TikTok use.' The Cronbach's alpha was 0.88.

Subjective well-being. To measure students' subjective well-being, we used the five-item World Health Organization Well-Being Index (WHO-5)(Topp et al. 2015). Items were assessed on a seven-point scale (1 = strongly disagree; 7= strongly agree). The Cronbach's alpha was 0.90.

Work engagement. To measure work engagement, we used an employee version of the Utrecht Work Engagement Scale (UWES–9S; Schaufeli et al. 2006). This scale has nine self-report items which are assigned into three subscales evenly: vigor (e.g., 'At my work, I feel bursting with energy'), dedication (e.g., 'My job inspires me'), and absorption (e.g., 'I am immersed in my work'). All items were scored on a seven-point rating scale (1 = never; 7= always). The Cronbach's alpha was 0.92.

Labile self-esteem. We used a five-item labile self-esteem scale to assess the tendency to experience fluctuation in self-esteem or perceived instability in self-esteem levels on a seven-point scale (1 = strongly disagree; 7= strongly agree)(Dykman 1998). An example item is 'My self-esteem shifts rapidly from feeling good about myself on one day to feeling bad about myself the next day.' The Cronbach's alpha was 0.88.

Analytic approach. Following guidelines from Nylund et al. (2007), we initially specified a two-profile solution, and then we gradually increased the number of the profiles until the model fit statistics did not warrant the loss of parsimony when another latent class was added. This approach is inductive and has been widely utilized in LPA. We used seven fit statistics to evaluate models: log-likelihood (LL), Akaike information criterion (AIC), Bayesian information criterion (BIC), sample-size-adjusted BIC (ABIC), Lo-Mendell-Rubin likelihood ratio test (LMR), bootstrap likelihood ratio test (BLRT), and entropy. For LPA fit statistics, there are no cutoff values. Instead, the ideal model has the fit statistics shown below: Values for LL, AIC, BIC, and ABIC should be lower than those for other profile solutions; entropy should be larger than those for other profile solutions, and LMR and BLRT should be significant ($p < .05$). Researchers should also take the theoretical implications of solutions into account while choosing the appropriate profile structure (Foti et al. 2012). We implemented LPA in the first phase as described above to establish the number of profiles that fit the data. Second, we confirmed the most probable membership of the profile based on the posterior distribution from the preceding stage. This step can be interpreted as "the estimated probability that each individual has of belonging to each of the profiles"(Morin et al. 2010, p. 66). Finally, auxiliary variables concerning the profiling solution are evaluated, according to the chance to be members of a particular class, and the classification error rate. These procedures attract attention to LPAs' major benefits over the conventional cluster analyses: considering inaccuracy with profiles categorization in analyzing relationships between profiles and other variables (Wang and Hanges 2011). Therefore, we analyzed the relationship between profile membership and outcome variables at this stage using the BCH command in Mplus(Asparouhov and Muthén 2014; Bakk and Vermunt 2016).

Results

Table 1 displays the means, standard deviations, and correlations for the Study 1 variables. Interestingly, we found positive correlations between gender and personal identity ($r = .11$, $p = 0.02$), negative mood management ($r = .15$, $p = 0.002$), positive mood management ($r = .16$, $p = 0.001$) and surveillance ($r = .19$, $p < 0.001$). And we also observed small negative correlations between age and negative mood management ($r = -.13$, $p = 0.011$), positive mood management ($r = -.11$, $p = 0.037$) and diversion ($r = -.12$, $p = 0.019$).

Table 1 Means, Standard Deviations, and Correlations of Variables in Study 1

Variables	M	SD	1	2	3	4	5	6	7	8	9	10	11	12
1. Gender	1.71	0.45												
2. Age	29.81	6.55	-0.07											
3. AD	2.56	1.14	0.08	-0.15**										
4. WE	5.15	1.00	-0.08	0.13*	-0.15**									
5. SWB	4.94	1.23	-0.02	0.09	-0.01	0.53**								
6. LSE	4.03	1.45	0.18**	-0.19**	0.28**	-0.33**	-0.32**							
7. PI	3.78	1.35	0.11*	-0.09	0.44**	0.12*	0.16**	0.19**						
8. NMM	4.36	1.39	0.15**	-0.13*	0.41**	0.07	0.03	0.31**	0.77**					
9. PMM	5.62	0.96	0.16**	-0.11*	0.34**	0.16**	0.16**	0.16**	0.57**	0.69**				
10. DI	5.40	1.05	0.08	-0.12*	0.24**	0.06	0.05	0.17**	0.41**	0.53**	0.59**			
11. SU	5.18	1.35	0.19**	-0.10	0.33**	0.12*	0.13**	0.17**	0.68**	0.62**	0.59**	0.43**		
12. SI	2.82	1.59	00.02	0.09	0.24**	0.22**	0.29**	0.03	0.70**	0.56**	0.42**	0.32**	0.44**	

Note. AD = TikTok addiction; WE = work engagement; SE = study engagement; SWB = subjective well-being; LSE = labile self-esteem; PI = personal identity; NMM= negative mood management; PMM = positive mood management; DI = diversion; SU = surveillance; SI = social interaction; Gender coded 1 = male, 2 = female; * $p < .05$. ** $p < .01$.

The fit statistics for possible latent profile structures are in Table 2. We chose the four profiles because they exhibited lower LL, AIC, BIC, and ABIC than two-, and three-profile solutions. Although the five-, and six-profile solution had slightly lower LL, AIC, BIC, and ABIC statistics in comparison to the four-profile solution, the entropy was lower. Moreover, other than using the fit indices, the four-profile solution's proportion was better balanced in terms of class proportions in comparison to the five- and six-profile solutions. Thus, we retained the four-profile structure. The scores of six TikTok use motive dimensions yield four profiles (see Figure 1A).

Table 2 Fit Statistics for Profile Structures in Study 1 and Study 2

No. of profiles	LL	FP	AIC	BIC	ABIC	LMR(p)	BLRT(p)	Entropy	CP
Study 1									
2	-3205.68	19	6449.36	6523.30	6463.02	0.0002	0	0.864	0.45/0.54
3	-3058	26	6168.00	6269.18	6186.69	0.0299	0	0.856	0.17/0.45/0.37
4	-2993.67	33	6053.33	6181.76	6077.06	0.0114	0	0.848	0.12/0.34/0.34/0.17
5	-2966.82	40	6013.64	6169.30	6042.40	0.1406	0	0.82	0.11/0.1/0.28/0.31/0.17
6	-2935.43	47	5964.85	6147.75	5998.64	0.044	0	0.83	0.08/0.22/0.18/0.09/0.24/0.16
Study 2									
2	-2710.19	19	5458.38	5529.80	5469.50	0	0	0.955	0.14/0.85
3	-2563.95	26	5179.89	5277.62	5195.20	0.0188	0	0.852	0.13/0.28/0.58
4	-2503.37	33	5072.73	5196.78	5092.10	0.0374	0	0.878	0.1/0.03/0.56/0.29
5	-2440.54	40	4961.07	5111.42	4984.60	0.0349	0	0.879	0.03/0.09/0.38/0.06/0.41
6	-2420.72	47	4935.44	5112.11	4963	0.3089	0	0.889	0.03/0.03/0.41/0.07/0.38/0.05

Note. LL = log-likelihood; FP = free parameters; AIC = Akaike information criteria; BIC = Bayesian information criteria; ABIC = sample-size-adjusted BIC; LMR = Lo-Mendell-Rubin likelihood ratio test; BLRT = bootstrapped log-likelihood ratio tests; CP = class proportions.

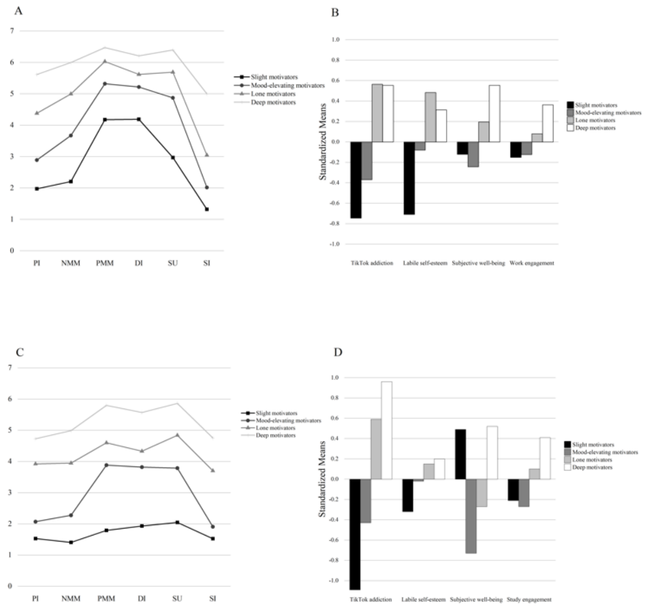

Figure 1 Latent Profile Structure and Standardized Means of Distal Outcomes.

Note. PI = personal identity; NMM= negative mood management; PMM= positive mood management; DI= diversion; SU= surveillance; SI= social interaction. The details of the four parts of the picture are as follows: A. Latent profiles for different employee TikTok users in Study 1; B. Standardized means of distal outcomes by latent profiles for Study 1; C. Latent profiles for different student TikTok users in Study 2; D. Standardized means of distal outcomes by latent profiles for Study 2.

Table 3 displays the descriptive information for the indicators in each profile. Class 1 constitutes 12.98% of the sample (N = 47) and represents individuals with the lowest personal identity, negative mood management, positive mood management, diversion, surveillance, and social interaction levels. Accordingly, we name this profile *slight motivators*. Class 2 represents 34.81% of the sample (N = 126) and we refer to it as *mood-elevating motivators* because these respondents report relatively higher levels of positive mood management, diversion, and surveillance but low levels of personal identity, negative mood management, and social interaction levels. Class 3 constitutes 34.25% of the sample (N = 124) and is termed *lone motivators*. This is because the motive of social interaction is the lowest and other motives are at a moderate but above-average level among participants of Class 3. Finally, Class 4 comprises 17.96% of the sample (N = 65) and these individuals report the highest values of the TikTok use motives. We name this profile *deep motivators*. In response to Research Question 1, these results suggest that there are quantitatively different motivators among employee TikTok users.

Table 3 Descriptive Information per Latent Profile for Study 1 and Study 2

Profiles	% of sample	PI		NMM		PMM		DI		SU		SI	
		M	S.E.	M	S.E.	M	S.E.	M	S.E.	M	S.E.	M	S.E.
Study 1													
Slight motivators	12.98	1.97	0.09	2.20	0.14	4.17	0.13	4.19	0.18	2.97	0.28	1.31	0.08
Mood-elevating motivators	34.81	2.89	0.09	3.67	0.14	5.32	0.11	5.21	0.12	4.87	0.10	2.01	0.10
Lone motivators	34.25	4.38	0.16	4.99	0.13	6.02	0.07	5.61	0.09	5.69	0.13	4.16	0.20
Deep motivators	17.96	5.61	0.14	5.99	0.11	6.47	0.09	6.21	0.12	6.39	0.10	4.99	0.34
Study 2													
Slight motivators	3.79	1.53	0.15	1.40	0.16	1.79	0.32	1.93	0.39	2.04	0.53	1.52	0.25
Mood-elevating motivators	10.41	2.07	0.16	2.27	0.21	3.88	0.18	3.82	0.17	3.78	0.30	1.90	0.21
Lone motivators	56.46	3.92	0.08	3.94	0.08	4.60	0.11	4.33	0.11	4.84	0.11	3.70	0.09
Deep motivators	29.34	4.72	0.14	4.98	0.18	5.79	0.14	5.57	0.16	5.86	0.11	4.75	0.24

On the basis of the four-profile structure, we examined the different distal outcomes. Table 4 and Figure 1B revealed that *slight motivators* were more likely to get the lowest TikTok addiction (M = 1.75, $S.E.$ = 0.13), labile self-esteem (M = 3.22, $S.E.$ = 0.21), work engagement (M = 5.03, $S.E.$ = 0.17), and second-lowest subjective well-being (M = 4.89, $S.E.$ = 0.19). *Mood-elevating motivators* had the lowest subjective well-being (M = 4.77, $S.E.$ = 0.12), second lowest TikTok addiction (M = 2.12, $S.E.$ = 0.07), labile self-esteem (M = 3.84, S.E. = 0.14), and work engagement (M = 5.06, $S.E.$ = 0.08). *Lone motivators* had the highest TikTok addiction (M = 3.06, $S.E.$ = 0.11), labile self-esteem (M = 4.41, $S.E.$ = 0.14), second highest subjective well-being (M = 4.81, $S.E.$ = 0.12) and work engagement (M = 5.09, $S.E.$ = 0.10). *Deep motivators* had the highest subjective well-being (M = 5.56, $S.E.$ = 0.15), work engagement (M = 5.55, $S.E.$ = 0.14), second highest TikTok addiction (M = 3.05, $S.E.$ = 0.17) and labile self-esteem (M = 4.24, $S.E.$ = 0.18).

Table 5 showed the results of a two-by-two comparison between profiles for each outcome. For TikTok addiction, only the comparison between *deep motivators* and *lone motivators* was not significant (p = 0.96). For labile self-esteem, the comparison between *mood-elevating motivators* and *deep motivators* (p = 0.08) and the comparison between *deep motivators* and *lone motivators* were not significant (p = 0.49) while other profile comparisons were significant. Moreover, for subjective well-being, the comparison between *mood-elevating motivators* and *slight motivators* (p = 0.62), the comparison between *mood-elevating motivators* and *lone motivators* (p = 0.82), and the comparison between *slight motivators* and *lone motivators* (p = 0.74) were not significant. Finally, for work engagement, the comparison between *mood-elevating motivators* and *deep motivators* (p < .001, χ^2 = 8.25), the comparison between *slight motivators* and *deep motivators* (p = 0.02, χ^2 = 5.18), and the comparison between *deep motivators* and *lone motivators* (p = 0.01, χ^2 = 5.72) were significant. To sum up, these results speak to the importance of Research Question 2, illustrating that different profiles of employee TikTok users relate to the different levels of distal outcomes.

Table 4 Descriptive Information for Distal Outcomes per Latent Profile

Outcomes	Slight motivators		Mood-elevating motivators		Lone motivators		Deep motivators	
	M	S.E.	M	S.E.	M	S.E.	M	S.E.
Study 1								
AD	1.75	0.13	2.12	0.07	3.06	0.11	3.05	0.17
LSE	3.22	0.21	3.84	0.14	4.41	0.14	4.24	0.18
SWB	4.89	0.19	4.77	0.12	4.81	0.12	5.56	0.15
WE	5.03	0.17	5.06	0.08	5.09	0.10	5.55	0.14
Study 2								
AD	1.23	0.12	1.89	0.16	2.91	0.08	3.28	0.14
LSE	3.34	0.37	3.64	0.26	3.81	0.08	3.86	0.15
SWB	5.38	0.52	4.17	0.30	4.63	0.09	5.42	0.13
SE	3.83	0.41	3.77	0.24	4.14	0.08	4.45	0.13

Table 5 BCH Results for Distal Outcomes for Study 1 and Study 2

Outcomes	Mood vs. Slight		Mood vs. Deep		Mood vs. Lone		Slight vs. Deep		Slight vs. Lone		Deep vs. Lone	
	χ^2	*p*	χ^2	*p*	χ^2	*p*	χ^2	*p*	χ^2	*p*	χ^2	*p*
Study 1												
AD	5.47	0.01	23.38	0.00	39.65	0.00	34.25	0.00	53.73	0.00	0.02	0.96
LSE	5.28	0.02	2.96	0.08	7.25	0.00	12.77	0.00	21.28	0.00	0.46	0.49
SWB	0.24	0.62	16.29	0.00	0.05	0.82	7.52	0.00	0.10	0.74	12.44	0.00
WE	0.01	0.89	8.25	0.00	0.06	0.80	5.18	0.02	0.09	0.75	5.72	0.01
Study 2												
AD	5.47	0.01	23.38	0.00	39.65	0.00	34.25	0.00	53.73	0.00	0.002	0.96
LSE	5.28	0.02	2.963	0.08	7.25	0.00	12.77	0.00	21.28	0.00	0.46	0.49
SWB	3.79	0.05	14.06	0.00	1.99	0.15	0.01	0.94	1.98	0.15	21.19	0.00
SE	0.01	0.90	5.85	0.01	1.95	0.16	2.06	0.15	0.55	0.45	3.433	0.06

Study 2

Method

Participants and procedure.

With the convenience sampling approach, we sent online invitations to about 1000 college students from three universities in Chinese mainland to participate in this study, and four hundred and eighty-seven (48.7%) students responded. We used Qualtric, an online survey tool, to collect data from those college students who signed informed consent before starting this study. Likewise, we used an attention check question to set the qualification of the participants, that is, at least one year of active users of TikTok (Douyin in China). The suvery questionnaires included a set of scales on the motives of TikTok use, TikTok addiction, labile self-esteem, subjective well-being, study engagement, and the demographic information.

We removed one hundred and seventy students (34.9%) due to serious missing values and failure in attention check. Therefore, a final sample of three hundred and seventeen participants (65.1%) was retained. Overall, the majority of participants were female (67.2%), and the average age was 19.18 years old (*SD* = 1.14). This study was approved by the Ethics Committee of the Business School at Hohai University.

Measures

TikTok use motives. As in study 1, we used a 26-item scale to measure participants' motives for TikTok use (Lonsdale and North 2011). The Cronbach's alpha was 0.89.

TikTok addiction. As in study 1, we used the short Smartphone Addiction Scale (Kwon et al. 2013) to measure TikTok addiction. The Cronbach's alpha was 0.91.

Subjective well-being. As in study 1, we applied the five-item World Health Organization Well-Being Index (WHO-5)(Topp et al. 2015). The Cronbach's alpha was 0.93.

Study engagement. We used the student version of UWES–9S to measure study engagement (Schaufeli et al. 2006). This scale also has three subscales with three items each: vigor (e.g., 'I feel strong and vigorous when I'm studying or going to class'), dedication (e.g., 'My study inspires me'), and absorption (e.g., 'Time flies when I am studying'). All items are scored on a seven–point frequency rating scale (1 = never; 7= always). The Cronbach's alpha was 0.93.

Labile self-esteem. As in study 1, we applied a five-item scale to measure labile self-esteem (Dykman 1998). The Cronbach's alpha was 0.82.

Results

Table 6 displays the means, standard deviations, and correlations for the Study 2 variables. The fit statistics for possible latent profile solutions are in Table 2. We chose the four profiles because they exhibited lower

LL, AIC, BIC, and ABIC than two- and three-profile solutions. And although six-profile solutions had lower LL, AIC, and ABIC statistics and higher entropy in comparison to the four-profile solution, the LMR statistics were not significant. While there was only a slight difference between four- and five profiles, combined with the result of Study 1, we retained the four-profile structure. Figure 1C provides a visual representation of the four profiles.

Table 6 Means, Standard Deviations, and Correlations of all Study 2 Variables

Variables	M	SD	1	2	3	4	5	6	7	8	9	10	11	12
1. Gender	1.67	0.47												
2. Age	19.18	1.14	-0.12*											
3. AD	2.84	1.21	-0.01	0.05										
4. LSE	3.79	1.21	-0.01	-0.05	0.30**									
5. SWB	4.85	1.28	-0.03	0.00	-0.08	-0.02								
6. SE	4.18	1.13	0.00	-0.07	-0.12*	-0.18**	0.35**							
7. PI	3.86	1.09	-0.01	-0.08	0.40**	0.11*	0.22**	0.18**						
8. NMM	3.97	1.18	0.00	-0.03	0.47**	0.12*	0.12*	0.10	0.74**					
9. PMM	4.77	1.11	0.08	-0.05	0.34**	0.04	0.18**	0.09	0.61**	0.67**				
10. DI	4.55	1.09	0.03	-0.06	0.32**	0.09	0.10	0.03	0.51**	0.62**	0.73**			
11. SU	4.92	1.23	0.10	0.00	0.19**	0.02	0.13*	0.06	0.63**	0.51**	0.65**	0.53**		
12. SI	3.73	1.41	-0.01	-0.09	0.24**	0.01	0.21**	0.19**	0.68**	0.57**	0.48**	0.41**	0.43**	

Table 3 displays the descriptive information for the indicators in each profile. Class 1 constitutes 3.79% of the sample (N = 12) and represents individuals with the lowest personal identity, negative mood management, positive mood management, diversion, surveillance, and social interaction levels. Accordingly, this profile is referred to as *slight motivators*. Class 2 represents 10.41% of the sample (N = 33) and we term it as *mood-elevating motivators* because the levels of positive mood management and diversion are relatively higher compared to other motives. Class 3 constitutes 56.46% of the sample (N = 179) and we name it *lone motivators*. Because the motive of social interaction is relatively low, while other motives representing individual needs are high. Finally, Class 4 comprises 29.34% of the sample (N = 93) and these individuals report the highest personal identity, negative mood management, positive mood management, diversion, surveillance, and social interaction levels. We name this profile *deep motivators*. Thus, the results are consistent with those of Study 1. In response to Research Question 1, these results suggest that there are quantitatively different motivators among student TikTok users.

In terms of outcomes, analyses yielded some pieces of evidence (Table 4, Table 5, and Figure 1D). For TikTok addiction and labile self-esteem, *slight motivators* were more likely to get the lowest TikTok addiction (M = 1.23, $S.E.$ = 0.12) and labile self-esteem (M = 3.34, $S.E.$ = 0.37), *mood-elevating motivators* had the second lowest TikTok addiction (M = 1.89, $S.E.$ = 0.16) and labile self-esteem (M = 3.64, $S.E.$ = 0.26), *lone motivators* were the second highest (M = 2.91, $S.E.$ = 0.08; M = 3.81, $S.E.$ = 0.08) and *deep motivators* got the highest TikTok addiction (M = 3.28, $S.E.$ = 0.14), and labile self-esteem (M = 3.86, $S.E.$ = 0.15). Moreover, *mood-elevating motivators* had the lowest level of subjective well-being (M = 4.17, $S.E.$ = 0.30), *lone motivators* were the second lowest (M = 4.63, $S.E.$ = 0.09), *slight motivators* were the second highest (M = 5.38, $S.E.$ = 0.52) and *deep motivators* had the highest level of subjective well-being (M = 5.42, $S.E.$ = 0.13). *Mood-elevating motivators* had the lowest study engagement (M = 3.77, $S.E.$ = 0.24), *slight motivators* were the second lowest (M = 3.83, $S.E.$ = 0.41), *lone motivators* were the second highest (M = 4.14, $S.E.$ = 0.08), and *deep motivators* had the highest level of study engagement (M = 4.45, $S.E.$ = 0.13).

Based on the four-profile structure, Table 5 revealed that the comparison between *lone motivators* and *deep motivators* for TikTok addiction was not significant ((p = 0.96). For labile self-esteem, the comparison between *mood-elevating motivators* and *deep motivators* (p = 0.08) and the comparison between *lone motivators* and *deep motivators* (p = 0.49) were not significant. For subjective well-being, the comparison between *mood-elevating motivators* and *deep motivators* ($p < 0.001$, $\chi^2 = 14.06$) and the comparison between *lone motivators* and *deep motivators* ($p < 0.001$, $\chi^2 = 21.19$) were significant. Finally, for study engagement, only the comparison between *mood-elevating motivators* and *deep motivators* was significant (p = 0.01, $\chi^2 = 5.85$). These results also provide insight into Research Question 2, illustrating that different profile solutions of student TikTok users related to different levels of outcome variables. In sum, Study 2 replicated successfully the findings of Study 1 on the profile solution and its distinct associations with distal outcomes.

General Discussion

By using a person-centered approach, we identified distinct profiles of TikTok use motives with a sample of 362 employees and a sample of 317 college students. The results revealed that a four-profile solution was more optimal than other solutions in the two studies. These distinct motive profiles may represent a subpopulation among people who use TikTok. Results also show a significant association between the latent profile membership and various outcomes, providing further evidence for a meaningful distinction among the identified subpopulation.

Theoretical Implications

First, our research contributes to the relevant literature on social media use (e.g., Kim 2017; Marengo et al. 2022; Whiting and Williams 2013). Our research emphasized the person-centered approach that had been underrated in previous research because this approach can bring new insights into the literature around social media use as the analytical method is changed from conventional variable-centered research to person-centered research (Zyphur 2009). Scholars have used LPA to explore the unobserved subpopulations in social media use by identifying specific profile solutions composed of variables along with social media use. The current research suggests that the person-centered approach can explicitly enrich our understanding of how specific configurations of social media elements work together to influence personal behavior.

Second, we contribute to the literature on TikTok use by exploring quantitatively distinct profiles of TikTok use motives (Research Question 1). Our two studies reveal the same profile structure. The *deep motivator* profile depicts a group of users who are at the highest level in all six dimensions of TikTok use motives. The motivational levels of the *lone motivator* are between those of the *deep motivators* and *mood-elevating motivators*. TikTok users in this profile have high levels of use motives of personal identity, mood management, diversion, and surveillance, yet have low levels of social interaction. One interpretation of this profile is that users care more about individual needs and less about social needs. The *mood-elevating motivator* profile is characterized by higher levels of positive mood management, diversion, and surveillance, and low levels of personal identity, social interaction, and negative mood management. People in this profile may be excellent emotional regulators who promote hedonic experience (Barta et al. 2023). Unlike the other three profiles, the *slight motivator* is characterized by the fact that all six motives of TikTok use are at relatively lowest levels of quantity. The shape of this profile varies slightly across our two studies. In Study 1, the line of the *slight motivator* profile showed an inverted U-shape, due to higher levels of positive mood management and diversion than other motives; in Study 2, the line of this profile was flatter and these motives were at approximately the same level. The motives of positive mood management and diversion were at a relatively higher level across the four profiles, indicating that they may be more prominent usage motives among employee-based TikTok users. In addition, an interesting finding is that social interaction motive is relatively lower across four profiles compared to other motives, which may be due to the design of TikTok; unlike other SMAs such as Facebook, Instagram, and WhatsApp, social interaction in TikTok is not an interaction between users and their social network, but rather with algorithmized self (Bhandari and Bimo 2020; Montag et al. 2021).

Third, we contribute to the literature on the consequences of TikTok use motive profiles (Research Question 2). Our findings indicated that TikTok users would progressively increase the assessment of TikTok addiction and labile self-esteem from *slight motivator* profile to *deep motivator* profile, indicating that a positive association possibly existed between TikTok use motives and TikTok addiction and labile self-esteem (Brougham 2021; Marengo et al. 2022). This means that the stronger the user's need for the six motives for TikTok use, the more likely it is that TikTok addiction and labile self-esteem will increase. Engagement and the profile of TikTok use motive show a similar pattern of relationship. We found that users would improve for both study engagement and work engagement from *slight motivator* profile to *deep motivator* profile. One interpretation of this result may be due to the motivational need for users to maintain a high level of positive mood management, diversion, and surveillance when using TikTok. These three needs may serve as energetic factors to enhance study and work engagement, echoing previous research on social media use (Gulzar et al. 2022; Oksa et al. 2021). Another interesting finding comes from subjective well-being. We found that TikTok users would show higher levels of subjective well-being in both *deep motivator* profile and *slight motivator* profile. The former has the highest levels of all six TikTok use motives and the latter has the lowest levels of motives. This seemingly contradictory finding may respond to the controversial results in previous studies (Kim 2017; Masciantonio et al. 2021). We believe that the quantitative level of use motives profile may explain why the inconsistent association between social media use and subjective well-being.

Finally, the research questions of our study were addressed in the sample of employees (Study 1) and college students (Study 2). Although we have replicated our profile structure in two different occupational contexts, we believe this four-profile solution is robust. The employee sample was recruited from Prolific and therefore had a Western cultural background (mainly the United States); the college student sample was recruited from local universities and therefore had a Chinese cultural background. In a word, our sample has both occupational and cultural differences. We found at least two differences in the main findings that emerged across the two studies. First, the percentage distribution of TikTok users in each profile was slightly different. In the employee sample, *mood-elevating motivators* were the majority of the sample (34.81%), followed by *lone motivators* (34.25%), *deep motivators* (17.96%), and *slight motivators* (12.98%). In the college student sample, *lone motivators* were the majority (56.46%), followed by *deep motivators* (29.34%), *mood-elevating motivators* (10.41%), and *slight motivators* (3.79%). This variation in the dominant profiles across different samples may be related to differences in the lifestyles of college students and employees. Employees use TikTok because they may need to regulate their emotions to relieve stress at work. For college students, in addition to regulating emotions, they may also need to represent themselves through TikTok. Despite the differences in the percentage distribution, the dominant motives of TikTok use between the two samples were similar. We found that employees and college students who use TikTok were mainly motivated by regulating happy feelings, seeking relaxation and entertainment, and learning real-time information, supporting TikTok's mission statement 'To inspire creativity and bring joy' (Mahendran and Alsherif 2020).

In addition, the relationship between each profile and the distal outcomes maintained a consistent pattern across the two samples. For instance, in the employee sample, TikTok addiction was highest for *deep motivators*, followed by *lone motivators*, *mood-elevating motivators*, and *slight motivators* orderly; in the college students sample, TikTok addiction and each profile kept the same relationship as in the employee sample. Subjective well-being was the highest and second-highest for *deep motivators* and *slight motivators* across the two samples. In the employee sample, work engagement was highest for *deep motivators*, while in the college students sample, study engagement was highest for *deep motivators* as well. However, the mean value of work engagement in the *deep motivator* profile was greater than that of study engagement in the same profile. These results indicate that the relationship between *deep motivators* and engagement may be stronger in the employee sample than in the college student sample.

Practical Implications

Our study yields several practical recommendations. First, based on our findings, we believe that it may be helpful for TikTok developers to think about which users' motives combinations are more effective in attracting a specific group of users and create conditions that help users work and enjoy life better. TikTok's developers and managers should be aware that it is important to identify users' subpopulations based on their needs, as this can help manage users' needs with precision. We suggest that this management of users' needs may strengthen TikTok's marketing strategy. Considering the dominant motives of positive mood management, diversion, and surveillance, developers can optimize TikTok's product design to enhance user experience. In addition, we found that social interaction was the lowest of all motives for TikTok use; this brings an implication that broadening the social network function in TikTok may be a direction to consider in the future (Omar and Dequan 2020).

Second, our outcome analyses indicate that TikTok users embedded within distinct profiles exhibit different levels of distal outcomes. Company managers and school administrators may consider whether measures can be introduced that can strengthen the effects of profile membership on subjective well-being and engagement as well as buffer its effects on TikTok addiction and labile self-esteem. For instance, introducing a self-help intervention program (Hou et al. 2019) may reduce TikTok addiction; avoiding non-work TikTok use at work (Syrek et al. 2018) may improve work engagement; building a healthy platform environment and self-control program (Cao et al. 2020; Labban and Bizzi 2022) may help improve self-esteem and subjective well-being.

Limitations and Future Directions

This current study has some limitations. First, based on U & G theory, we only used a six-factor framework of gratification (Lonsdale and North 2011; McQuail et al. 1972) to explore the optimal profile solution to TikTok use motives. As we all know, however, scholars have proposed different versions of TikTok use motives (e.g., Falgoust et al. 2022; Meng and Leung 2021; Scherr and Wang 2021). Hence, there is a possibility that different profiles of motives quantitatively or qualitatively may exist if different gratification frameworks are used. Future research should consider alternative profile solutions with another framework of TikTok use motives.

Second, we did not model the antecedents of the profile solution in this current study. For instance, it may be informative to consider the individual differences of TikTok users (e.g., big-five personality, self-concept, emotional regulation, social comparison orientation) and environmental factors (e.g., culture, TikTok features, TikTok community) given their importance in the TikTok use process.

Finally, this current study consists of a cross-section analysis using two sets of online survey data. Although we investigated the profile indicators of TikTok use and the consequences of the motive profiles, causality cannot be found. When considering time-lagged designs, an interesting research question would be how TikTok uses motives' profiles to change over time. To address this issue, a longitudinal statistical technique like latent transition analysis (Ryoo et al. 2018) can be used to identify whether participants stay in an assigned latent group, or transition to a different latent group over time. This analytic technique will offer new insight into TikTok users' membership.

Conclusion

In the current study, we used LPA to better understand how to define TikTok users' subpopulations through interaction patterns of their use motives. The findings demonstrate that (a) different quantitatively distinct profiles of TikTok use motives do consistently exist, and (b) latent profile memberships differentiate TikTok addiction, labile self-esteem, subjective well-being, and engagement outcomes. Our results shed light on the benefits of adopting a person-centered approach to better explain the unobserved heterogeneity of the TikTok users' population.

Acknowledgements

Acknowledgements This study was supported by the Fundamental Research Funds for the Central Universities (B220207022).

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