



AI-Powered Social Media Platforms and Their Effect on Emotional Well-Being

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ABSTRACT

The rise of social media applications based on artificial intelligence created by the use of AI has completely changed the cyber-communication environment as it has raised a lot of questions concerning the psychological effects of using these applications among the younger population groups, including college students. This paper has explored how the use of AI-driven social media platforms can influence the emotional health of students at a university in Lahore, Pakistan. A cross-sectional survey design was used as a quantitative research design whereby 420 students who were selected through convenience sampling across six universities (three public and three private) in Lahore were used to collect the data. The warwick-edinburgh mental well-being scale (WEMWBS) was applied to measure emotional well-being, and self-reported frequency and engagement indicators on platforms such as Tik Tok, Instagram Reels, YouTube Shorts and Snapchat were used to measure AI-powered platform use. The instruments were adjusted to the Pakistani cultural situation, and all of the items were found to be very internally consistent (.78-91 Cronbach alpha). Data analysis was done using demographic analysis, descriptive statistics, Pearson correlation and partitioning through structural equation modeling (SEM) using AMOS 26 and SmartPLS 4.0. The findings showed that passive content consumption with AI involvement and emotional well-being were significantly negatively correlated ($\beta = -.34, p < .001$), whereas active and creative intervention showed positive correlations ($\beta = .22, p < .01$). Several pathways were modulated with age, gender and type of university. The structural model had good fit indices (CFI = .96, RMSEA = .054, SRMR = .062). Policymakers in digital literacy, mental health and responsible AI design policy in higher education in Pakistan can use these findings to implement changes in these areas.

Keywords

artificial intelligence-based social media, emotional well-being, university students, Pakistan, structural equation modeling, online interactions, mental health, WEMWBS

INTRODUCTION

The world digital ecosystem has been changing in an unprecedented manner with the introduction of artificial intelligence (AI) into social media platforms. No longer passive, user-generated content, modern podiums like Tik Tok, Instagram, YouTube, and Snapchat have since developed these platforms into highly engaging AI-driven platforms capable of curating, recommending, and personalizing content with remarkable accuracy. On these platforms, machine learning, deep neural networks, natural language processing, and behavioral analytics are used to predict and influence preferences and make highly personalized digital experiences so personalized that it is becoming more and more important to disengage (Auxier and Anderson, 2021; Twenge, 2017). Although the technological advancement has been rich in terms of the communication, creativity, and accessibility of information, empirical studies are emerging in growing numbers to reinforce the idea that the advancement has such serious lasting effects on the life of ordinary users, young adults, in particular.



One of the groups of most heavily digitally engaged demographic cohorts in the world is represented by university students. They are a generation that has been brought up in an age of accelerated social media growth, commonly known as digital natives, and they are overexposed to AI-led content systems at a time in their development when identity is forming, academic anxiety arises, and they are particularly sensitive to social comparison (Andreassen et al., 2017; Vannucci et al., 2017). In Pakistan, the use of smartphones has grown at a notably high rate, and the use of social media among the young population of between 18 and 24 has risen exponentially, with apps like Tik Tok, Instagram and Youtube taking control of the youth daily activities (Digital Rights Foundation, 2022; Kemp, 2023). Regardless of this, the psychological impacts of AI-curated information processing on emotional health in Pakistan university students are underreported in the literature.

Emotional well-being including aspects of positive affect, life satisfaction, psychological functioning, and lack of psychological distress is an imperative factor in academic accomplishment, interpersonal relations, and long term mental health roots (Huppert and So, 2013; Keyes, 2005). Studies held in the Western culture have reported correlations between the use of social media and low levels of emotional well-being, such as higher levels of anxiety, depression, loneliness, and negative self-image (Fardouly et al., 2015; Primack et al., 2017; Twenge et al., 2018). But this has been shaken by more recent scholarship, which holds that it is the nature of the engagement (passive consumption or active creation) that mediates the outcomes and that cultural contexts mediate these relationships in noteworthy ways (Orben & Przybylski, 2019; Valkenburg et al., 2021).

The adventures that AIs are tasked with in particular: the endless scroll, personalized layer of hyper-recommendations, autoplay, and algorithmic delivery of notifications, bring about dynamism that differentiates today's platforms with those of the older versions of social media. Such characteristics are actually designed to maximize time on the platform, and would capitalize on psychological vulnerabilities like the need to gain social approval, the feeling of missing out (FOMO), and novelty-seeking behavior (Alter, 2017; Montag et al., 2019). The personalization of content implemented into AI can produce a filter bubble and an echo chamber that reduces the information diversity and at the same time boosts emotionally activating information, such as information about the social comparison, idealized body images, and performative success (Pariser, 2011; Zhao et al., 2022). These processes bring significant questions about whether AI-enabled platforms empowered as agents of social connectedness and imaginative expression or become agents of emotional dysregulation.

Digital social spaces in this case, in the Pakistani context, interact greatly with the cultural conventions on gender roles, family expectations and social honor. Pakistanian women studying at universities have their own pressures regarding appearance standards, marriage impositions, and cultural dystopian that can aggravate the adverse impact of social comparison materials produced by AI (Zaman et al., 2021). Concurrently, male students can have various types of digital pressure that pertain to performance, professional performance, and social status. The combination of AI-mediated affordances of platforms with these culturally-specific pressures renders Pakistani university students especially significant and underrepresented in the literature on social media and mental health worldwide.

The available literature is mostly from the Western, educated, industrialized, rich, and democratic (WEIRD) societies, with a little relevance to South Asian cultural contexts where digital media consumption is influenced by the unique socioeconomic factors, family dynamics and education demands (Henrich et al., 2010). The Pakistani system of higher education as well can be described in terms of gross disparities between the environments of public and private universities in terms of socioeconomic makeup, academic culture, access to digital infrastructure, and services related to mental health. Those disparities in institutions can lead to various phenomena of social media usage and emotional impact which have not been studied yet (Hassan et al., 2020).

Considering these gaps, the current study sought a methodologically sound quantitative research exploring the use of AI-powered social media platforms and their impact on the emotional well-being of university students in both public and private universities in Lahore, Pakistan. The research used a validated measurement tool and cross-sectional survey research design, exceptional sampling protocol, involving six universities, and employing sophisticated statistics tools (including structural equation modelling) to analyse direct and indirect relationships. This study aimed to generate insights into actionable, nuanced evidence that educational policy makers, mental health practitioners, platform designers and academic administrators in Pakistan and the rest of South Asian nations could use due to the moderating influencing demographics and the consideration of passive versus active engagement of AI-platforms.

Three main research questions guided the study: (1) to evaluate the trends and degree of use of AI-powered social media platforms among Lahore university students; (2) to determine the degree of emotional well-being among the identical sample of students; and (3) to explore the nature, the direction and the strength of the relationships between the indicators of AI platform use usage and the dimensions of emotional well-being, including modulating effects of demographic factors of The results serve a growing literature that advocates culturally contexted research of methodological advanced studies on the psychological implications of AI-mediated social contexts.



LITERATURE REVIEW

Emotional Well-Being and use of Social Media

Emotional well-being has been confirmed to be greatly significant in relation to the social media use and the literature on this has extensively revealed both positive and negative links in relation to social media use varying in type, intensity and context. According to the large-scale longitudinal analyses of the data in the Monitoring the Future study, Twenge et al. (2018) discovered that adolescents who spent five or more hours a day on an electronic device were 66% more prone to have at least one suicide risk factor than those who devoted one hour a day to the same issue. In the same manner, Primack et al. (2017) examined the statistics of 1,787 young adults in the United States and found that the percentage of the 125th percentile of individuals who used social media had much higher chances of experiencing depression and anxiety than that in the 97.5 th percentile. Vannucci et al. (2017) replicated these results with a more specific sample of a university student, and the results indicated that the level of depression symptoms was much more strongly relevant to high levels of social media use as compared to other factors, such as demographics and total screen time.

Subsequent scholarship has however cast doubts on the story of the exclusively destructive impacts of social media. A model of within-person variability put forward by Valkenburg et al. (2021) implies that the outcomes of social media on well-being are incredibly personal, and variables that mediate these results include social comparison orientation, self-esteem, and content viewed. Orben and Przybylski (2019) interpreted analysis on specification curves on several large datasets and made a variety of conclusions: the relationship between social media use, on the one hand, and well-being, on the other hand, is significant but is not large in its purpose sufficiently small in its strength as the use of glasses or potatoes. Their research revealed the risks of creating an exaggerated picture of the negative consequences of social media without considering the complexity of underlying mechanisms and individual variations.

One of the moderating variables has become the difference between passive and active social media use as a crucial attribute in recent research. In an experimental study, Verduyn et al. (2015) have shown that passive Facebook use resulted in affective well-being declines but active use did not. Passive mode of its usage involves scrolling, watching content left by other people, and seeing their post but the content itself does not involve any personal interaction, thus facilitating upward social comparison and envy, especially when content consumed features perfect lives, successes, or bodies. Active features like posting, comment, sharing, and messaging are likely to encourage social connection and mutual communication, which can overcome loneliness, and emotional control (Burke et al., 2010; Fardouly et al., 2015). These differences are especially applicable when it comes to AI-enabled websites that actively enhance passive consumption by use of autoplay and infinity scroll functionality.

Scanty yet emerging studies have also emerged in the South Asian setting that aim at capturing the psychological impacts of the social media. The authors, Hassan et al. (2020), studied the problem of social media addiction and its connection to psychological well-being in Pakistani university students and showed that the social media addiction negatively related to the psychological well-being of the students, especially females. In a sample of Pakistani women, Zaman et al. (2021) investigated the problem of body image and the connection between its evaluation and the use of Instagram, stating that the desire to see idealized beauty images was strongly linked to body dissatisfaction and low self-esteem. Although these are helpful studies, they failed to make a distinction between the features of the AI-powered and traditional social media and the use of tested well-being tools with known psychometric factors in the Pakistani setting.

AI within Social media sites

Introducing AI to social media platforms are a qualitative change in the functionality of digital content environments and their impact on the users. Modern AI-driven platforms will utilize recommendation algorithms that recognize large inflows of behavioral data, such as watch time, scroll patterns, likes, shares, search history, location information, and even device orientation, to create detailed models of user preferences and present very specific content (Covington et al., 2016; Zhao et al., 2022). One of the most advanced content recommendation systems in the mass-market social media, the For You Page (FYP) algorithm of Tik Tok has been observed to reach the impressive level of personalization in the initial hours a new user spends on the website, building an environment filled with immersive and highly captivating content, which has been linked to unusual consumption habits, specifically termed as addictive frequently (Montag et al., 2021; Omar & Dequan, 2020).

Algorithms Studies of algorithmic content curation have expressed worries in terms of its ability to create emotional states to optimize engagement at the peril of user health. A study of more than 689,000 Facebook users conducted by Kramer et al. (2014) proved that emotional contagion is possible with manipulation of the News Feed content algorithmically and exposure to more positive or negative posts generates respective changes in the emotional expression of the users. Although this study caused an extreme level of ethical controversy, the results illustrated a tremendous impact that the use of AI-powered content curation could have



on the emotional states on an enormous scale. Later studies have further demonstrated that these algorithms confirmatively rank emotive arousing, outrage, and anxiety-inducing content since emotive arousing content results in more engagement measures that generate loops of feedback, which may allecontrollably intense degradation of emotional welfare (Brady et al., 2017; Stieglitz and Dang-Xuan, 2013).

The psychosocial processes that allow the AI platform features to impact emotional well-being are social comparison theory, fear of missing out (FOMO), technoference, and dopaminergic cycles of reinforcement. The social comparison theory, initially proposed by Festinger (1954) and later developed by a number of other authors, is the concept of interpreting self-possession, beliefs, and skills (or rather their own) based on the comparison with other individuals. Algorithms centering AIs that accumulate content with ideal comparisons over and over again are harmful to the self esteem and emotional stability in specific ways that are especially harmful in self esteem and emotional well-being (Fardouly & Vartanian, 2015; Vogel et al., 2014). The all-pervasive fear of not being having pleasant experiences but missing it, FOMO, has been found to mediate the connection between social media use and the emotional implications such as anxiety, loneliness, and dissatisfaction with life (Przybylski et al., 2013; Reer et al., 2019).

The AI platform design, and, consequently, its characteristics (like counts, comment notifications, follower metrics, and content performance analytics) are based on the concept of variable reward schedules, modeled on the principles of behavioral psychology, as well as operant conditioning. These characteristics lead to the formation of random patterns of reinforcement that become neuropsychologically stimulating and related to compulsive checking and inability to disengage self-regulation (Alter, 2017; Andreassen et al., 2016). This has led to the so-called technoference, or the penetration of the use of technology into inter-personal relationships and everyday life, which has been connected to lower quality of relationships, less in-person socializing, and lower outcomes in emotional well-being (McDaniel and Radesky, 2018; Sbarra et al., 2019).

Measures of Emotional Well-Being and Theory

Emotional well-being is a multidimensional construct though it has been conceptualised in a number of theoretical frameworks that apply in the present study. Dual-continuum model according to Keyes (2002) opines that mental health and mental illness are both related and different dimensions and that emotional well being, positive affect, life satisfaction and psychological functioning are separate positive poles which are not merely a lack of psychopathology. The self-determination theory by Ryan and Deci (2000) offers a complementing theory, which proposes that well-being is anchored on the satisfaction of three universal psychological needs, which include autonomy, competence and relatedness. The use of social media in ways that compromise these needs (by creating addiction, subjecting people to negative comparisons or replacing the emotionally shallow engagement of the digital realm with an authentic relational one) can thus be predicted to worsen emotional well-being by theoretically identified mechanisms.

Since its initial working phases by Tennant et al. (2007), which were validated via various culture-specific and linguistic backgrounds, the Warwick-Edinburgh Mental Well-Being Scale (WEMWBS) has become one of the most common and most widely used validated measures of emotional well-being in population research. WEMWBS is a questionnaire comprised of 14 items addressing positive affect, rewarding interpersonal relationships and positive psychological functioning rated on a five-point Likert scale. It is especially appropriate in the case of research involving students of universities due to its psychometric features such as high internal consistency and test-retest reliability, as well as its construct validity in diverse populations (Clarke et al., 2011; Ng Fat et al., 2017). Noteworthy, the WEMWBS is modified and proven to work in South Asian settings, making it possible to implement the approach in the current Pakistani research (Kashyap et al., 2020).

A number of theoretic models have been advanced to answer the question of the specific pathways in accordance with which a social media use influences the well-being regarding emotions. According to the displacement hypothesis, time on social media replaces the time to perform other activities that are more likely to be healthy, including physical activity, sleep and in-person social communication (Twenge, 2017). It is based on the work of Festinger (1954) and grounded in his idea of the social comparison hypothesis; it underlines the importance of negative comparisons that are made possible by controlled content in the social media. The stimulation hypothesis is that the use of social media can be beneficial and can be used to support social well being as it has a source of social support, artistic expression and information access (Valkenburg and Peter, 2009). According to the reinforcement sensitivity theory using digital media, the sensitivity to rewards and punishment can influence the extent to which social media can positively influence well-being; nonetheless, the effect of this usage depends on the individual agency of reward and punishment sensitivity (Blackwell et al., 2017). Bringing these frameworks together, the current paper framed the features of AI platforms as environmental affordances that can engage these mechanisms with different strengths based on the personal user features and patterns of interactions.

The literature to date has been using structural equation modeling to test these multivariate relationships that are complex in the research of social media. SEM enables you to estimate multiple regression equations, and can be used to test both direct and indirect relationships between variables, mediated by additional variables, and given



latent construct error. Mediation channels via self-esteem, as well as social comparison orientation, FOMO, and loneliness have been confirmed in studies of the application of SEM in social media and well-being research (Charoensukmongkol, 2018; Lee et al., 2016). The current work used SEM as the main analytical approach to reflect the structural complexity of relations between the indicators of AI platform usage and the dimensions of emotional well-being in the Pakistani context of university students.

METHODOLOGY

Research Design

This study was done using a quantitative cross-sectional survey design. Such a design was deemed acceptable as the main purpose was to quantify and describe the correlation between the use of AI-powered social media platforms and emotional well-being in a single point in time within a specific group. Timely cross-sectional designs are very popular in social science studies researching attitudinal and behavioral constructs of large populations of students because of its efficiency, cost-effectiveness, and applicability of multivariate statistical methods such as structural equation modeling (Creswell & Creswell, 2018; Field, 2018).

Population and Sampling

The sample size was constituted by the present student population of the undergraduate and postgraduate programs in Lahore, Pakistan universities. The city of Lahore was chosen as the study area since it is considered to be the most populated urban educational center in Pakistan and is home to the highest number of universities in Pakistan and is an institutional rich area both in the public and the private sectors. A total of six Universities got to be included: three public universities and three privileged universities. This was to be done through stratified institutional selection to ensure that they pick variation in the profiles of students with different socioeconomic backgrounds, the academic cultures, and available digital resources in the public and the privatized learning facilities.

The use of convenience sampling was based on practical factors such as the permission to access the sampled students, lack of time, and the lack of all-enrolled students sampling frames within the chosen institutions. Although convenience sampling provides certain limitations of selection biases, which in turn limits investigative results in the context of the general student population, it is frequently used in quantitative studies based on students and it is justified in situations when probability sampling is not achievable due to logistical reasons (Etikan et al., 2016). The power analysis using G power 3.1 to obtain the medium effect size ($f, 2 = .15$), alpha of .05 and power of .80 in multiple regression with a maximum number of predictors of 15 gave that a minimum required sample size of 175 participants. The set consistency threshold of 420 was calculated to consider possible non-responses, non-completed questionnaires, the fulfillment of the suggested 10:1 ratio between the cases and parameters represented in structural equation modeling (Hair et al., 2019). Inclusion criteria were that participants should be current students with age between 18-30 years, and they should rank themselves as active users of at least one AI-powered social media platform, and have at least 30 minutes per day active use.

Instrumentation

A set of structured self-administered questionnaires were created and used as the main data collection tool. This questionnaire consisted of four parts. The first section was a question on the demography where the individual was asked their age, gender, year of study, program of study where they were studying, bracket of monthly household income, and the type of university (either a public or a private university). A 12-item self-report scale created in this paper was used to evaluate the use of AI-powered social media platforms in the second part. Questions were used to measure the frequency of use in the number of platforms used on a daily basis (in hours), the number of platforms used regularly, which specific AI functionality is being used (recommendation algorithms, autoplay, filters, AI-generated content), and subjective measures of engagement: the perception of being presented with content suited to their interests and the frequency of having the desire to scroll further. The items were treated with five-point Likert scale types of items between 1 (Never/Strongly Disagree) to 5 (Always/Strongly Agree). In the third section, the Warwick-Edinburgh Mental Well-Being Scale was used (WEMWBS; Tennant et al., 2007), a 14-item scale, which is a valid instrument that measures positive emotional functioning, positive relationships, and positive psychological functioning in the two weeks before the assessment. Items will be rated on a five-point scale (None of the times) to 5 (All of the times), and items that affect total scores greater will represent greater levels of emotional well-being. A fourth section comprised of an 8-item scale of social comparison tendencies modified after the Iowa-Netherlands Comparison Orientation Measure (INCOM; Gibbons and Buunk, 1999) to provide measures of individual differences in the tendency to social comparison as a possible mediator variable.

All the scales were translated into Urdu through a forward-backward translation method in order to guarantee linguistic and cultural similarity. Three bilingual academic experts in the field of psychology and communication studies did an independent review of the Urdu translations and agreed upon differences. Pilot test on 35 university students that were not part of the main study was done to determine the clarity, cultural



factor- appropriateness and initial psychometric character of the questionnaire. Questions which showed item-total correlations less than 0.30, and questions which were not clear in terms of cultural understanding, were amended before the actual main data collection exercise.

Data Collection Procedure

One academic year (2023-2024) was studied during eight weeks to collect data. The six chosen universities saw research assistant who have been trained in research ethics, methods of administering questionnaires and rights of participants visit the schools on the predetermined days. The questionnaires were dispersed in the common areas during nontimes in university canteens, library reading rooms and common areas. Involvement was purely voluntary and no motivation was given. All participants were given an information sheet before they completed the questionnaire with detailed information about the purpose of the study, their entitlement to withdraw without penalty, confidentiality of information and anonymized group presentation of the findings. All subjects were provided with informed consent that was written down. Questionnaires were completed and the collected questionnaires were obtained as soon as they were filled so as to avoid any loss of data. 445 questionnaires were sent out with 428 being returned. Upon the above screening processes of incomplete responses and outliers, 420 questionnaires were kept to be analyzed, implying a useable response rate of 94.4.

Ethical Considerations

The research followed the principles of ethics provided by the Declaration of Helsinki and was given official ethical clearance by the Institutional Review Board of the institution of the respective lead researcher before it commenced the research. All the data obtained were put in encrypted files that were restricted to the key research team. All stages of data processing and reporting ensured anonymity of participants. Because the research involved measuring delicate psychological aspects, the research information sheet contained contact-addressing data of university counseling services and gave participants information on how they could seek professional help in the event they were upset because of their reactions.

Data Analysis

Analysis was done with IBM SPSS Statistics Version 26 and AMOS Version 26 with a supplement of SmartPLS Version 4.0 to perform partial least squares structural equation modeling, as a robustness test. The analytical process was accomplished in a number of sequential steps. Descriptive statistics in the form of frequencies, percentages, means and standard deviations were used to summarize the demographic characteristics. All substantive scale items and composite scores were first of all worked on descriptive statistics. The multi-item scales analyzed were all subjected to a reliability test done by Cronbach alpha coefficient, whose value of .70 or more is deemed as acceptable and a value of .80 or more as good (Nunnally, 1978). The construct validity was determined by confirmatory factor analysis (CFA) in AMOS, which evaluated the convergent validity by using the average variance extracted (AVE) and composite reliability (CR), and discriminant validity using Fornell-Larcker criterion.

Pearson product-moment correlation coefficient was used to look at the bivariate relationship between indicators of AI platform use and emotional well-being scores. To analyze the differences in mean scores in emotional well-being among the subgroups of demographic groups, independent samples t-tests and one-way ANOVA were used. It was used to perform hierarchical multiple regression to ascertain the distinct share of affective well-being, which can be explicated by the variables of AI platform usage, beyond the impact of the demographic covariates. To test the hypothesized structural model, AMOS was done through structural equation modeling using maximum likelihood estimates. A combination of fit indices such as Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA) with 90 percent confidences, and Standardized root mean square Residual (SRMR) were used to evaluate model fit. Observation was done to test mediation pathways by booting sampling the bootstrap procedures (5-000 bootstrap samples) to obtain bias-adjusted confidence intervals of indirect effects. Assessments of multicollinearity were done by evaluating the variance inflation factors (VIF) and the common method bias was measured utilizing the single factor test by Harman and common latent factor method in AMOS.

ANALYSIS

Participant Characteristics

Finally, a total of 420 valid questionnaire responses were used in the analysis study. The sample comprised 231 female participants (55.0%) and 189 male participants (45.0%), with ages ranging from 18 to 30 years ($M = 21.34$, $SD = 2.18$). Most of the respondents were undergraduate students ($n = 312$, 74.3%), and 108 postgraduate students (25.7%). There was a balance in terms of type of institution, with 210 (50.0) participants recruited in a public and 210 (50.0) participants in a private university, which is based on the balanced sampling approach. The highest number ($n = 168$, 40.0) belonged to second year or third year bachelors. Concerning household income, 38.1% had monthly household incomes below PKR 50,000, 43.3% between 50000 and 150,000, and 18.6% above PKR 150,000, which is representative of the mixed public-private university sample with regard to the economic composition.



Variable	Category	Frequency (n)	Percentage (%)
Gender	Female	231	55.0%
	Male	189	45.0%
Age	Range	18–30 years	—
	Mean (M)	21.34	—
	Standard Deviation (SD)	2.18	—
Education Level	Undergraduate	312	74.3%
	Postgraduate	108	25.7%
Institution Type	Public Universities	210	50.0%
	Private Universities	210	50.0%
Year of Study	2nd / 3rd Year (Bachelor)	168	40.0%
	Other Years	252	60.0%
Household Income	Below PKR 50,000	—	38.1%
	PKR 50,000 – 150,000	—	43.3%
	Above PKR 150,000	—	18.6%

Social Media Usage Patterns

The descriptive analysis of the use of the AI-powered social media platforms showed that Tik Tok was the most used ($n = 298, 70.95\%$), then Instagram ($n = 289, 68.81\%$), followed by YouTube ($n = 276, 65.71\%$) and Snapchat ($n = 198, 47.14\%$). The average frequency of use of platforms was 3.12 ($SD = 1.08$). The average hours of daily usage were reported to be 4.67 ($SD = 1.94$) with the average duration of female students being significantly higher than that of male students ($M = 4.98$ vs. $M = 4.29; t(418) = 3.41, p = .001$). The students of the private university said that they used it every day more than students of the public university ($M = 5.12$ vs. $M = 4.22; t(418) = 4.67, p < .001$). Passive consumption practices, which are characterized as scrolling, viewing and watching without posting or interacting, were the most common form of interaction with 68.3 percent of respondents describing passive activities as more than half the total time on social media. Exposure to AI-personalized content was also self-reported, and the perception that the content they were presented with was specifically relevant to their interests (78.1% agree/strongly agree), as well as the feeling that they were often tempted to scroll further than they intended to consume the content (72.4%).

Platform	Frequency (n)	Percentage (%)
TikTok	298	70.95%
Instagram	289	68.81%
YouTube	276	65.71%
Snapchat	198	47.14%

Reliability and Validity Analysis

The measurement scales were proven to have acceptable to excellent internal consistency as reflected by reliability analysis in terms of Cronbach alpha. WEMWBS total scale proved to be very reliable ($\alpha = .91$), which aligns with the psychometric analyses of this tool that were conducted previously with the same instrument. The AI Platform Usage Scale was proved to be highly reliable ($\alpha = .84$). Social Comparison Orientation scale had acceptable reliability ($\alpha = .78$). All items that were retained had item-total correlations greater than .35 and none of the items had a corrective alpha value that would enhance the scale reliability when deleted, and justify the suitability of the scale in terms of its item selection.

Confirmatory factor analysis confirmed that there is a three factor measurement model of the hypothesized latent constructs. All indicators factor loadings were above .50 with most above .65 helping to show convergent validity. Extracted values of average variance were more than the .50 criterion of all constructs (WEMWBS AVE = .61, AI Usage AVE = .53, Social Comparison AVE = .51) and composite reliability scores were above .70 (WEMWBS CR = .94, AI Usage CR = .88, Social Comparison CR = .83). The Fornell-Larcker criterion was used to determine the discriminant validity: the square root of AVE of each construct was greater than its correlation with all the other constructs. The shared latent specifying test showed that the common method bias was about 18.7 percent of the total variance, which is less than the 25 percent mark, which would be considered as problematic by Harman single-factor test, and showed that no single measure could understand the greater part of overall data variance.

Scale	Cronbach's Alpha
WEMWBS	.91
AI Platform Usage Scale	.84
Social Comparison Orientation	.78

Validity Analysis (CFA Results)

Construct	AVE	CR
WEMWBS	.61	.94



AI Platform Usage	.53	.88
Social Comparison	.51	.83

Descriptive Statistics and Correlations

The average score of WEMWBS total in the entire sample was 44.31 (SD = 8.76), and both the average scores were moderate concerning the level of emotional well-being reported in the context of university students (Kashyap et al., 2020). Female students reported lower mean emotional well-being scores than male students ($M = 43.12$ vs. $M = 45.74$; $t(418) = 2.98$, $p = .003$), and public university students reported higher mean emotional well-being than private university students ($M = 46.03$ vs. $M = 42.59$; $t(418) = 3.87$, $p < .001$). One-way ANOVA showed that emotional well-being scores varied significantly between the income brackets, $F(2, 417) = 8.43$, $p < .001$ with post-hoc Tukey tests showing that students in the lowest income bracket obtained a significantly lower emotional well-being scores compared to students in higher income brackets ($p < .01$).

In Pearson analysis, it was found that WEMWBS total score had a negative progression with total daily social media usage time ($r = -.31$, $p < .001$), which proved that the more time one spent on with platforms per day, the less their emotional state was healthy. The passive use of time, in particular, exhibited a more negative relationship with WEMWBS total score ($r = -.38$, $p < .001$) and active engagement time had a small positive relation ($r = .18$, $p < .001$). Emotional well-being had a negative correlation with the number of AI-based platforms used on a regular basis ($r = -.24$, $p < .001$). Perceived content personalization had negative correlation with emotional well-being ($r = -.27$, $p < .001$) and desire to scroll past the planned use had negative correlation ($r = -.33$, $p < .001$). The relationships between social comparison orientation and emotional well-being ($r = -.44$, $p < .001$) and passive AI platform consumption ($r = .39$, $p < .001$) were found to be negative indicating that social comparison can be a mediating factor between the use of AI platform and emotional well-being.

Descriptive Statistics (Emotional Well-being)

Group	Mean (M)	SD	t/F value	p-value
Overall Sample	44.31	8.76	—	—
Female Students	43.12	—		
Male Students	45.74	—	2.98	.003
Public Universities	46.03	—		
Private Universities	42.59	—	3.87	< .001
Income (ANOVA)	—	—	8.43	< .001

Correlation Matrix

Variables	r	p-value
Daily Usage Time → Well-being	-.31	< .001
Passive Consumption → Well-being	-.38	< .001
Active Engagement → Well-being	.18	< .001
Number of Platforms → Well-being	-.24	< .001
Personalization → Well-being	-.27	< .001
Scrolling Urge → Well-being	-.33	< .001
Social Comparison → Well-being	-.44	< .001
Social Comparison → Passive Use	.39	< .001

Hierarchical Multiple Regression

Hierarchical multiple regression was used to test the incremental predictive validity of the variables of AI platform use on the emotional well-being over and above demographic covariates. Block 1 loaded demographic demographics (gender, university type, year of study, household income) contributing to 11.4 percent of the variance in WEMWBS total scores, $F(4, 415) = 13.32$, $p < .001$, and $R^2 = .114$. In Block 2, indicators of AI platform use (daily usage hours, proportion of passive consumption, number of platforms, perceived personalization, scrolling urge) were included, which created a substantial increase in the explained variance, $87 = 21.48$, $p < .001$. The final model accounted for 30.1% of total variance in emotional well-being, $F(9, 410) = 19.13$, $p < .001$, $R^2 = .301$. Some of the individual predictors of the final model were: passive consumption proportion ($\beta = -.29$, $p < .001$), scrolling urge ($\beta = -.24$, $p < .001$), perceived content personalization ($\beta = -.18$, $p = .002$), daily hours of usage ($\beta = -.16$, $p = .007$), and household income ($\beta = .19$). The variance inflation factors were between 1.12 and 2.34 meaning that there was no multicollinearity problem.

Hierarchical Multiple Regression Analysis

Predictor	Beta (β)	p-value
Passive Consumption	-.29	< .001
Scrolling Urge	-.24	< .001
Perceived Personalization	-.18	.002
Daily Usage Hours	-.16	.007
Household Income	.19	.001



Structural Equation Modeling Results

AMOS 26 was used to test the hypothesized structural model based on maximum likelihood estimation. The original structural means comprised direct relations between AI platform usage (a second-order latent variable that consists of passive consumption, active engagement, and AI feature dependence) and emotional well-being mediated by the social comparison orientation. The direct connections between demographic variables and the endogenous constructs were also defined in the model. The initial model fit was evaluated and modifications indices were checked; two theoretic underpinning covariances relating to residuals were loosened, and a better model with an excellent overall measurement was drawn: $\chi^2(df = 214) = 389.4, p < .001$; CFI = .962; TLI = .951; RMSEA = .044(90). These values also met the suggested acceptable thresholds of model fit (Hu and Bentler, 1999).

The direct negative association of AI platform use with emotional well-being ($\beta = -.34, p < .001$) was a significant result of the structural model: more AI-driven platform usage reduced emotional well-being when other variables of the model were considered. The fact that the social comparison orientation was affected by the use of AI platforms showed a significant and positive impact (Without annotation: $B = .42, p < .001$), which shows that innovative use of AI platforms was more likely to be attributed to the increased social comparison orientation. The social comparison orientation, in its turn, showed that it had a significant negative direct impact on the emotional well-being ($\beta = -.28, p < .001$). Mediation analysis with 5,000 samples (bootstrap) validated the established significant indirect impact of AI platform use on emotional well-being through the social comparison orientation (indirect effect = $-.118$; 95 percent CI: $-.167$ to $-.072$) to demonstrate that social comparison partially mediated the relationship between AI platform use and emotional well-being.

The relationship between passive AI platform consumption and emotional well-being was moderated by gender: the negative relationship between passive consumption and emotional well-being was significantly greater among female participants ($\beta = -.41, p < .001$) compared to male participants ($\beta = -.26, p = .002$) as the interaction term in a multi-group SEM analysis showed (χ^2 difference test: $6.83 = -$). The relationship also depended on university type, where students at private universities were much stronger in their negative relationship between AI platform use and emotional well-being than students in public universities. A robustness check was done through SmartPLS 4.0 PLS-SEM analysis, which confirmed the pattern of findings with similar path coefficients and bootstrapped-indirect effects, indicating the stability of the structural model both in covariance-based and variance-based SEM analyses.

DISCUSSION

The results of this paper present strong quantitative data that the use of AI-driven social media platforms is linked to the lack of emotional well-being in university students in Lahore, Pakistan, and that the nature of engagement due to active use versus passive, algorithm-controlled use is an at least significant confounding variable. These findings are generally in line with theoretical perspectives that focus on the psychological costs of passive social media use (Verduyn et al., 2015) and empirical literature that reports negative correlations between social media use and emotional well-being in student populations (Primack et al., 2017; Vannucci et al., 2017). The theoretical centrality of social comparison mechanisms in the determination of how AI-curated content environments convert to emotional impacts is further supported and confirmed by the fact that such a correlation is modified by social comparison orientation, which in turn means that subsequent proposals suggesting that algorithmic personalization enhances social comparison by generating idealised, high-performing and aspirational content through systematic surfacing has their theoretical basis.

It is noteworthy and culturally relevant that passive AI-driven consumption was demonstrated to be more strongly negatively correlated with emotional well-being in female, as compared to male students of this sample. Since cultural norms regarding the appearance of females, desirability in matrimony, and performance in the society are especially salient in the Pakistani context, the interactions between exposure to the AI-enhanced idealized images and lifestyle content and underlying cultural vulnerabilities might contribute more of the psychological costs to the female students. This agrees with the results by Zaman et al. (2021) on the same in a Pakistani sample and extrapolates to the context of AI-driven platform functionalities. The fact that negative effects were stronger in private university students than in public university students deserves follow-up research, but could be a result of differences in exposure patterns, such as that students in more affluent educational institutions are more likely to use smartphones and data intensively and, hence, exhibit stronger social comparison reference groups, or may be due to differences in patterns of exposure to social comparison. The high-quality model fit measures and the robustness of the results between AMOS and SmartPLS mode of analysis endorse the belief in the reliability and validity of the structural relationships discovered under the two indicators.



CONCLUSION AND RECOMMENDATIONS

In this work, researchers determined the presence of significant negative correlations between use of AI-powered social media platforms, especially passive watching algorithmic content, and emotional well-being amongst university students in Lahore, Pakistan. Social comparison orientation played a significant role as a partial mediator of this relation, and gender and university type acted as moderators of an important nature. Findings highlight the necessity to study the types of digital engagement separately and not to consider social media use unitary and the importance of using culturally contextualized research on AI-mediated psychological outcomes in non-Western cultures.

The recommendations are in the following based on the findings. University administrations need to incorporate progressive digital literacy programs during orientation and student wellness programs with the ability to make students more aware of AI recommendation engines, AI influence, and social comparison processes. The processes and practices in mental health amid university counseling settings must include screening problematic patterns of passive social media use as part of regular well-being evaluations and especially among female students. National and institutional policymakers ought to demand a higher degree of transparency on the side of AI platform operators about the design of the recommendation system and its psychological effects, through the current body of evidence, and the findings of Pakistani settings. During the design of AI recommendation systems, platform designers are encouraged to focus more on user well-being measures and engagement optimization, such as capabilities that facilitate purposeful use patterns and restrict passive habits that are not obligatory. Longitudinal designs should be used in future research to determine the directionality of identified associations over time, investigate the potential mediating role of resilience factors that could fortify against the adverse effects of AI platforms and undertake cross-cultural comparative research to extrapolate Pakistani results to South Asian and global contexts.

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