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Impact of AI-Based Content Filtering on Self-Esteem: Moderating Role of Digital Literacy

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ABSTRACT

The use of artificial intelligence (AI)-driven content filtering systems has become an intrinsic part of the design of modern-day digital platforms, which then influence the information landscapes that users are exposed to at a previously unheard-of level of accuracy and magnitude. Although the use of these systems has been widely implemented, their psychological implications, especially concerning the self-esteem of users, have not been properly studied in empirical research, especially in non-Western learning institutions. This paper was aimed at evaluating how AI-based content filtering affects the self-esteem of university students in Islamabad, Pakistan, and digital literacy as a modulating factor. The design used was a quantitative cross-sectional survey design and a total of 384 students were sampled and included in six universities (three government and three privately owned) in Islamabad through convenience sampling. The Rosenberg Self-Esteem Scale (RSES) was used to measure self-esteem, 10 modified items based on validated digital experience frameworks were used to measure AI-based content filtering perception and the Digital Literacy Scale (DLS) created by Hiller Spires and others was used to measure digital literacy. There was a good internal consistency among the instruments with Cronbach alpha values ranging between.79 and.93. The analyses of the data were performed with the help of the IBM SPSS Statistics Version 26 which helped to conduct preliminary analyses and with the help of SmartPLS Version 4.0 and AMOS Version 26 which helped to conduct the structural equation analysis and test the moderation. The findings showed a significant and negative correlation between AI-based content filtering perception and self-esteem (beta = -.31, p =.001). Digital literacy moderated this relationship in a significant manner, whereby the students who reported to be more digitally literate showed less negative effects of AI filtering perception on self-esteem (interaction beta =.26, p <.01). Model fit indices were satisfactory (CFI = .958, RMSEA = .047, SRMR = .061). The implications of these findings are on the education of digital literacy, counseling in universities, and responsible design of AI filtering systems in educational digital ecosystems.

Keywords
content filtering using AI, self-esteem, digital literacy, moderation, university students, Pakistan, structural equation modeling, Islamabad.

INTRODUCTION

The growth of AI technologies in the digital communication infrastructure has essentially changed the processes of information curation, dissemination, and experience of information on an individual user level. The AI-driven content filtering system, including algorithmic real-time recommendation systems, personal content curation engines, automated content moderation systems and predictive content delivery systems, is currently an invisible but ubiquitous mediator between users and informational ecosystems of modern digital platforms. Social media such as YouTube, Tik Tok, Instagram, Facebook, Twitter/X, LinkedIn, and news aggregation platforms use advanced machine learning models, collaborative filtering, and natural language processing algorithms to decide

what content is viewed by individual users, when, at what frequency, and how it resonates emotionally (Covington et al., 2016; Rader and Gray, 2015; Zhao et al., Although the underlying principle of these systems is that they are supposed to maximize user experience by personalizing and optimizing relevance, their psychological implications on individual users is a field of increasing academic interest.

Self-esteem, loosely understood as how one, subjectively, assesses their own value and the affective orientations related to that value, is a constructive unit in the field of psychological study with a long history of being associated with mental well-being, academic success, social functioning, and satisfaction with life (Baumeister et al., 2003; Rosenberg, 1965). The modern digital landscapes, which are defined by the existence of social comparison, the presence of public performance metrics, including likes and the number of followers, exposure to idealized self-presentations, and feedback loops inherent in the platform designs have been found potentially significant to self-esteem, especially in higher education institutions among young adults (Vogel et al., 2014; Valkenburg et al., 2021). Nevertheless, the particular role of AI based content filtering in self esteem output as compared to the overall impact of the use of social media has been relatively under-empirically investigated.

The self-esteem shaping of AI-based content filtering systems takes place in a number of theoretically consistent directions. To start with, by algorithmically revealing the content that mirror and exacerbate existing interests, behaviours and social networks of users, these systems generate immersive social comparison spaces that are filled with content that is specifically tuned to be stimulating- and thus frequently comprised of aspirational, idealised, or high-performing exemplars with which users will compare themselves unfavourably (Festinger, 1954; Fardouly Second, AI filtering systems affect self-esteem by a phenomenon known by scholars as the curated self paradox: as users are driven to continuously optimize their outward self presentation and algorithms drive the amplification of others outward self presentations, an environment of constant impression management and comparison is created (Chou and Edge, 2012; Vogel et al., 2014). Third, the lack of transparency of AI filtering systems, users usually know little about the ways in which a piece of information is being offered to them, can make one feel powerless, less independent, and less in control of their informational world, which in turn has been shown to be linked with self-esteem (Bandura, 1997; Langer, 1975).

As a possible moderating variable in the interplay between exposure to digital media and psychological consequences, it has been suggested that digital literacy (i.e., those competencies, skills and critical understandings with which individuals can effectively and critically utilize digital technologies and digital information spaces) will moderate the relationship between the two variables (Buckingham, 2007; Eshet-Alkalai, 2004; Hiller Spires et al., More digitally literate people could also exhibit a higher awareness of how algorithms are curated, have a better ability to critically assess algorithmically chosen content, a more advanced set of self-regulatory mechanisms to control digital intake, and less prone to the social comparison mechanisms enabled by AI filtering systems. Digital literacy, in this model, is more of a mental and critical resilience rather than a technical skill to potentially dangerous aspects of digitally mediated digital space (Park, 2012; Livingstone, 2004).

Islamabad context is particularly a good place to carry out this investigation. Islamabad, being the federal capital of Pakistan and one of the largest centres of higher education, boasts a vibrant and fast expanding student body of universities, which have seen an increased rate of smartphone uptake and social media incorporation in the last ten years. The social media industry in Pakistan has experienced a phenomenal growth, with an active social media population of more than 71 million as of 2023 and a growth in digital activity in the country surpassing any other South Asian country (Kemp, 2023). University students in Islamabad are a socioeconomically heterogeneous group that cuts across the highest ranks of the publicly research-based system of Pakistan and a developing market of privately-run universities, both of which are within different digital cultures and have varying access to digital literacy education. It is this institutional diversity, combined with the demographic attributes of students working in digital settings in a psychologically sensitive environment of identity formation and academic socialization, that has rendered Islamabad university students an important and underrepresented population in the world literature of AI-mediated psychological outcomes.

Although there is an increasing global interest in the psychological impact of algorithmic content systems, only a small sample of studies has been carried out in South Asian settings (especially in the United States, the United Kingdom, and Western Europe) where the digital media use behavior is determined by unique cultural values, socioeconomic factors, language, and educational systems (Henrich et al., 2010). However, Pakistani studies on social media and its impact on psychological well-being have been increasing over the last few years but have seldom considered the specific role of AI-based content filtering as a single variable and have rarely tested digital literacy as a theoretically-grounded moderator of the psychological effects of filtering (Hassan et al., 2020; Zaman et al., 2021). This research filled these gaps by using a strict quantitative design that employed validated measurement tools, a representative multi-institutional sampling plan and a sophisticated structural equation modeling to test both direct and moderated correlations.

The study had three main research objectives (1) to evaluate how AI-based content filtering perception positively affects self-esteem among Islamabad university students; (2) to determine whether digital literacy mediates the relationship between AI-based content filtering perception and self-esteem; and (3) to determine

differences in AI filtering perception, digital literacy, and self-esteem across gender, university type, and year of study. There were two main hypotheses put forward: H1, that the perception of AI based content filtering would be significantly and negatively related to self-esteem; and H2, that digital literacy would mediate this negative effect with higher degrees of digital literacy students showing lesser negative effects of AI filtering perception on self-esteem. The results are added to the growing interdisciplinary literature on the interface of artificial intelligence research and educational psychology and digital media research, and have practical implications on curriculum developers, mental health researchers, higher education leaders, and platform designers.

LITERATURE REVIEW

AI-Based Content filtering: algorithms and experience

AI-enabled content filtering systems are technologically advanced collections of machine learning models, behavioral analytics systems, and natural language processing systems, which run on perpetual basis on digital platforms to select informational contexts to individual users. These systems fundamentally operate on behavioral data streams such as click histories, viewing durations, scroll patterns, search queries, frequency of interactions, device properties, temporal usage patterns and relationships in social networks to create probabilistic models of user preferences and provide content they predict to be the most engaging (Covington et al., 2016; Pariser, 2011). The shift in the previous rule-based filtering models to modern deep learning models has radically enhanced the level of sophistication and accuracy of personalization, and facilitates platforms to understand user preferences with minimal initial behavioral indicators and optimize recommendations at an astonishing rate (Zhao et al., 2022).

The psychological research on the user experience of AI-based content filtering is described by a few distinct features that are used to characterize the user experience. The best-researched is the so-called filter bubble phenomenon which was initially theorized by Pariser (2011) and then testable in various platforms and among various populations. Filter bubbles refer to the nature of algorithmic curation that creates customized informational spaces that augment and confirm the views, likes and social identity of users, reducing access to various or challenging viewpoints. Although empirical studies on strong filter bubble effects have disputed them (Guess et al., 2018; Moller et al., 2018), the overall idea of algorithmic personalization of content to produce asymmetric and personally-targeted content environments is empirically established. A large-scale experiment on Facebook by Bakshy et al. (2015) showed that cross-cutting ideological content was significantly less exposed to with algorithmic ranking, but individual choice was a moderating factor.

Psychologically, the experience of the content filtered with an algorithm has been linked to both positive and negative results based on the type of content experienced and individual attributes of users. The positive effects of content personalization have been reported as an increase in information relevance, a decrease in cognitive load during information search, increased exposure to information that is relevant to their interests, and easier access to niche communities and social support networks (Sundar and Marathe, 2010; Thorson and Wells, 2016). Examples of negative outcomes are reported in the empirical literature, such as an increased social comparison, epistemic closure due to filters, a sense of informational agency diminished, content that systematically elicits feelings of anxiety or inadequacy, and what researchers have called algorithmic anxiety, a diffuse fear about the degree to which their digital environment is being influenced by opaque automated systems (Bucher, 2018; Eslami et al., 2015; Gran et al., 2021)

Importantly, the awareness of users and their attitudes towards AI-based content filtering exhibit significant variability and affect the psychological results. A seminal study by Eslami et al. (2015) found that most users of Facebook were unaware of the fact that it was an algorithmically-curated News Feed, and that, on learning of this curation, users had multifaceted emotional reactions, including surprise, interest, and uneasiness. Later studies have revealed that algorithmically aware users have altered interaction with the content of the platform, showing an increased assessing attitude towards content suggested by the algorithms and lower sensitivity to the effects of emotional contagion (Gran et al., 2021; Kawakami et al., 2022). These results highlight the significance of perceived algorithmic transparency and user agency as moderating variables in studies about AI filtering and psychological outcomes, and guide the theoretical placement of digital literacy as a moderator in the current study.

Artificial Intelligence Content-Filtering and Self-Esteem

The connection between the use of algorithms to curate digital spaces and self-esteem has been discussed in a number of theoretical frameworks which shed light on specific psychological processes. The most widely used theory is the social comparison theory (Festinger, 1954), which was elaborated by other scholars, such as Buunk and Gibbons (2007) and Vogel et al. (2014). This theory suggests that people compare themselves with the other people they deem important to them in order to consider their own attributes such as appearance, achievement, social status, and lifestyle. In particular, the social comparison processes are amplified by AI-based content filtering systems since they are used to surface high-engagement content in a systematic manner, which is disproportionately represented as aspirational, aesthetically polished, and socially validated exemplars that may

serve as unfavorable standards of comparison to an average user (Fardouly and Vartanian, 2015; Vogel et al.,2014).

Vogel et al. (2014) engaged in experimental study that revealed that the exposure of upward social comparisons on social media yielded significant declines in self-assessments of opinion ability, self-worth, and physical appeal. These results were generalized to Instagram by Fardouly et al. (2015), who found that viewing algorithmic content with idealized image of the body was linked to body dissatisfaction and reduced appearance-related self-esteem, especially in young women. Notably, these researches were performed in contexts where AI recommendation systems already existed, implying that the results were self-esteem effects caused by algorithmically-selected comparison opportunities, as opposed to passively-experienced social information. According to more recent studies, research has specifically studied how recommendation algorithms influence comparison content, revealing that personalized recommendation systems increase exposure to social comparison content by up to 40% over chronological content feeds (Lup et al., 2015; Sheldon et al., 2017).

In addition to social comparison, AI-based content filtering can have an impact on self-esteem by systems associated with perceived autonomy and informational control. The self-determination theory (Ryan and Deci, 2000) is a theory that postulates that the psychological well-being and good self-esteem depend on the satisfaction of the three basic psychological needs such as autonomy, competence and relatedness. Perceivedly opaque, manipulative, or autonomy-undermining, algorithmic content curation can disappoint these needs, leading to negative self-assessments and low self-esteem. The study by Bucher (2018) reported the experiences of users of algorithmic invisibility (the feeling that their content is being pushed aside or diminished down the ranking by the platform algorithm) in relation to a sense of inadequacy and lower sense of social efficacy. The results are indicative that the subjective experience of AI filtering, such as perceived algorithmic bias, content suppression, and lack of informational agency are potential contributors to self-esteem declines via mechanisms independent of social comparison.

Culturally-mediated between algorithmically-filtered online content and self-esteem in the Pakistani and even broader South Asian context, appearance, social status, family honor, educational performance and gender performance are culturally-mediated determinants of these two facets. Zaman et al. (2021) determined that exposure to idealized beauty material on Instagram was related to a high level of body image dissatisfaction and low self-esteem in Pakistani women with the social comparison being a major mediating factor. Similar culturally specific self-esteem vulnerabilities in response to algorithmically enhanced social comparison material have been reported in studies in India and Bangladesh, such as pressures to matrimonial desirability, academic prestige, and conspicuous consumption (Arora et al., 2019; Islam and Hossin, 2016). Nonetheless, none of the existing studies have investigated the unique role of AI-based content filtering as a predictor variable, specifically, in relation to self-esteem among Pakistani university students, which is an important gap that needs to be filled by the current study.

Moderating Variable: Digital Literacy

Digital literacy has been both theorized and operationalized in various forms throughout the diverse interdisciplinary literature in the fields of information science, education, communication studies, and psychology. Initial visions focused on technical skills and functional competencies-the skill to operate digital tools, navigate in the online world and handle digital information in an effective manner (Eshet-Alkalai, 2004). The more recent frameworks have broadened the construct and include critical dimensions such as the capacity to judge the credibility and bias of the information that is found online, comprehend the technical and economic logic of the digital platforms, safeguard personal privacy and data, communicate well in digital space and engage reflectively in the social and ethical consequences of digital technologies (Buckingham, 2007; Park, 2012; Ng, 201 Hiller Spires et al. (2008) have come up with a comprehensive digital literacy framework that highlights three general competency areas, namely: finding and consuming digital content, creating digital content, and communicating and sharing through digital means, and each of the competencies has been operationalized in validated measurement tools.

Digital literacy theoretically should mediate the connection between AI-based content filtering and self-esteem in a number of ways. First, digitally literate people tend to have awareness of the algorithmic curation systems, and its logics, which allow them to take a more critical and detached approach to the content that has been suggested algorithmically (Livingstone, 2004; Park, 2012). This hyper-awareness of the algorithms can diminish the extent to which the content of comparison surfaced by the algorithm is uncritically absorbed as a true depiction of the social reality. Second, digital literacy involves information verification and source evaluation skills that can allow people to put into perspective the idealized information that is often furthered by AI systems, diminishing its effects on self-evaluative mechanisms. Third, digitally literate users have more self-regulatory skills in the digital context, such as more purposeful habits of content consumption, a higher ability to disengage on the platform, and a reduced vulnerability to engagement-maximizing design features that support passive consumption (Cho et al., 2020; Reinecke et al., 2014).

Digital literacy as a mediator of psychological impact of social media is an empirically growing and limited evidence, especially within non-Western conditions. Cho et al. (2020) discovered that critical media literacy mediated the association between social media use and body image dissatisfaction in Korean university students, whereby a higher level of media literacy had a much-reduced detrimental impact. Livingstone and Helsper (2007) showed that having digital literacy skills was linked to more subtle and less emotional responsive use of online content amongst British teens. Park (2012) discovered that algorithmically aware social media users in a sample of South Koreans had reported a higher self-esteem and a reduced tendency to engage in social comparison in comparison to algorithmically unaware social media users. In a sample of young adults, Maksl et al. (2015) reported that media literacy competencies mediated the connection between negative body image and exposure to social media. Collectively, these results give empirical confirmation to the theoretical hypothesis which asserts that digital literacy mediates the psychological effect of AI-curated digital environments, but direct assessments of this mediation in the scenario of AI-based content filtering, in particular, are scarce.

The theoretical framework used to justify the current research combined social comparison theory (Festinger, 1954), self-determination theory (Ryan and Deci, 2000) and Uses and Gratifications perspective (Katz et al., 1973) to place AI-based content filtering as an environmental affordance that triggers self-evaluative processes, and digital literacy as a cognitive and competency- This integrative model assumes that the harmful effects of AI-driven content filtering on self-esteem will be contingent on the digital literacy levels, with increased levels of digital literacy playing the role of a psychological buffer, which mitigates the harmful effects of algorithmically-curated social comparison contexts.

METHODOLOGY

Research Design

The design of this investigation was a quantitative cross-sectional survey. The choice of this design was due to the study objectives that necessitated measurement of perceptions, attitudes, and psychological characteristics at a given time in a specified population (university students). Moderation analysis of psychologically measured variables allows survey designs that best support moderation analysis to be cross-sectional survey designs, which allows simultaneously measuring predictor, moderator, and outcome variables and estimating interaction effects using structural equation modeling (Creswell and Creswell, 2018; Hair et al., 2019). Quantitative method has been used to enable rigorous testing of hypothesis, application of reliable measurement tools with known psychometric properties and generalization of the results to the larger population of interest using statistical inference.

Population and Sampling

The study target population was the present undergraduate and postgraduate students of the universities in Islamabad, Pakistan. Islamabad was chosen as the study site because it is the federal capital of Pakistan and is densely populated with a variety of both public and privately run universities, and because it is representative of the educated youth in Pakistan, based on the number of students studying in the city. A sample of 6 universities was chosen purposely to capture institutional diversity on the public-private spectrum namely, three public universities (Quaidi Azam University, Federal Urdu University of Arts, Science and Technology and International Islamic University Islamabad) and three private universities (COMSATS University Islamabad, Bahria University and Capital University of Science and Technology). This stratified sample was meant to ensure a diversity in socioeconomic student demographics, access to digital resources, academic culture and previous experience of digital literacy education in the institutional types.

The main sampling method was convenience sampling since it was necessary due to practical limitations in institutional accessing, the lack of extensive enrollment registers that can be used to conduct a probability sampling, and time limitations of data collection process. Although convenience sampling has drawbacks in the form of limitations on selection bias, limiting strict probabilistic generalization, it is commonly used and accepted in quantitative research with a student population, and it is suitable to the analytical goals of the present study, which did not require prevalence estimates at a population level, but instead sought to analyze the relational and structural parameters (Etikan et al., 2016). The target sample was calculated as a result of power analysis in G*Power 3.1 which was 384 participants. The desired amount of predictors and interaction terms (specified: f 2 =.15) and the desired significance level (.05), power (.80), and a maximum number of predictors and interaction terms (12) indicated that the required sample size was 155. The 384 target was established as more than the minimum number of paths needed to conduct SmartPLS PLS-SEM analysis (ten times the maximum number of paths directed on one construct in the model) (Hair et al., 2019). The inclusion criteria were the presence of at least one AI-enabled content or social media where participants spend at least 30 minutes a day, the participants were required to be actively enrolled students aged between 18 and 30, and finally the participants had to give voluntary informed consent.

Instrumentation

The structured self-administered questionnaire was used to gather data in four sections. The initial part was the demographic section that required the respondents to provide demographic details such as age, gender, year of

study, academic program, household income range and the type of university (public or private). The second part was used with a 10-item tool known as the Rosenberg Self-Esteem Scale (RSES; Rosenberg, 1965), which is a universally-accepted gold standard self-esteem scale in the field of psychology. The RSES measures global self-esteem using four-point Likert scale of 1 (Strongly Disagree) to 4 (Strongly Agree) and there are five positively worded and five negatively worded items, though the latter should be reverse-scored before being computed into a composite score. The more the total scores the more the self esteem. RSES has shown strong psychometric reliability among the populations of different cross-cultural backgrounds and has proven to be useful with the populations of Pakistani university students (Akhtar and Mukhtar, 2015; Schmitt and Allik, 2005).

The third section involved measuring AI-based content filtering perception with a 10-item adapted scale that was created in this study. The items were created by conducting a systematic review of the available instruments that measure the algorithmic awareness, personalization perception, and AI filtering experience and using items of the Algorithmic Awareness Scale (Rader and Gray, 2015), the Perceived Personalization Scale (Sundar and Marathe, 2010), and the Platform Transparency Perception items created by Eslami et al. (201 Questions evaluated four dimensions; perceived personalization intensity (The content I see on social media feels specifically tailored to my interests and preferences), algorithmic transparency awareness (I understand how social media platforms determine the type of content to show me), perceived informational control (I feel in control of the type of content that appears in my social media feeds), and social comparison facilitation (The content recommended to me by social media often makes me compared to others). Each of the items was rated using a five-point Likert scale rating 1 (Strongly Disagree) to 5 (Strongly Agree).

The fourth section included items that measured digital literacy with a Digital Literacy Scale (DLS) adapted by Hiller Spires et al. (2008) and refined by Ng (2012), including 18 items that measured three main domains of digital literacy, such as technical-functional skills (the ability to use digital tools and navigate digital environments), information literacy (the ability to find, analyze, and critically evaluate It was rated on a five point Likert scale; 1 (Not at all skilled/capable) to 5 (Extremely skilled/capable). This scale has shown acceptable-good psychometric qualities with a variety of samples of different cultures, including South Asian populations (Hassan et al., 2021). The questionnaire was translated into Urdu (forward-backward translation protocol) to maintain linguistic and cultural equivalence in all the three sections of the questionnaire. Three academic bilingual experts in digital communication and psychology reviewed the items translated and consensus discussion solved any discrepancies in translation. A pilot study with 40 students not part of the main sample was carried out to determine the clarity of items, cultural appropriateness and initial psychometric performance with one of the items of the AI filtering scale being revised in terms of clarity before the main data collection.

Data Collection Procedure

The data collection was in a span of seven weeks in the academic semester of Spring 2024. Questionnaires were given by a group of four trained research assistants in the six universities involved. Standardized administration protocols were given to research assistants about how they were required to approach potential participants, what to say about the purpose of the study, offering consent forms, giving and accepting questionnaires and dealing with queries by the participants. The questionnaires were also given in common places that can be easily accessed such as university cafeterias, library study halls and student lounges at non-class hours to ensure that the diversity of potential respondents was maximized. Participation was all voluntary, there was no payment and any participant had the right to drop out at any point without penalty. No personally identifying information was captured in any of the questionnaires, and they were anonymous. There were 410 questionnaires that were distributed. Questionnaires were also carefully filtered on the basis of completeness, eliminating those with less than 10% of the items answered or those that showed patterns of systematic responding (e.g., all items rated the same on reverse-scored scales). After the screening, 384 questionnaires were retained to be analyzed and this represented a retention rate of 93.7 which was usable.

Ethical Considerations

This research was carried out in complete compliance with the ethical principles of the Declaration of Helsinki and was officially cleansed of ethical issues by the Institutional Ethics Committee of the institution where the first author works before starting the collection of data. Written informed consent was given by all participants after reading an information sheet, which outlined the purpose of the study, voluntary nature of participation, lack of identifiable personal data recording, secure data storage measures and the intended academic use of the results. The participants were told that they could drop off the study at any time without giving reasons and did not face any adverse effects. Since self-esteem, which was measured in the study, was a psychologically sensitive measurement, the information sheet contained contact details of university counseling services, and those participants who showed signs of acute distress in the course of data collection were quietly given referral details by the research assistants who were trained on how to identify such signs.

Data Analysis Strategy

All the data collected were keyed in IBM SPSS Statistics Version 26 where they were pre-processed and analyzed initially. Accuracy of data entry was checked by means of double-entry procedures of a random 15 per cent subsample of the data, with the result that the error rate of data entry was less than 0.5, and this was considered to be reasonable. All substantive variables that had descriptive statistics were calculated (means, standard deviations, skewness, and kurtosis indices). The test of normality was done by the use of Kolmogorov-Smirnov and Shapiro Wilk tests that were complemented with the visual analysis of frequency histograms and Q-Q plots. Frequency distributions were used to do demographic analyses, independent samples t-tests to compare means between binary groups, and a one-way ANOVA to compare means between more than two groups with eta-squared effect sizes reported. Cronbach alpha was used to analyze reliability of all multi-item scales and the values of less than 0.70 were considered acceptable and the ones of less than 0.80 were considered good.

In AMOS 26, confirmatory factor analysis (CFA) was used to evaluate the measurement models of convergent and discriminant validity, using factor loadings, average variance extracted (AVE), and composite reliability (CR) and the Fornell-Larcker and heterotrait-monotrait (HTMT) ratio of correlations, respectively. Harman single-factor test and the marker variable technique were considered as the methods of evaluating common method bias. The SPSS was used to calculate Pearson correlation coefficients between the main study variables to test the bivariate relationship between the variables before structural analysis. Both AMOS 26 (covariance-based SEM) and SmartPLS 4.0 (partial least squares SEM) were used to test the hypothesized structural relationships, with the latter as the main analysis tool due to its ability to test moderation relationships through the inclusion of interaction terms and its ability to work with non-normally distributed data (typical of psychological survey research) (Hair et al., 2019 The moderation analysis in the SmartPLS was done through the product indicator method to generate the AI Filtering × Digital Literacy interaction term with 5,000 bootstrap samples used to produce bias-corrected confidence intervals of all path coefficients. CFI, TLI, RMSEA and SRMR indexes were used to determine model fit and cut-off criteria were put in place (Hu and Bentler, 1999).

ANALYSIS

Sample Characteristics

The analytical sample used was finally a sample of 384 university students in six different universities in Islamabad. The sample included 196 female participants (51.0%) and 188 male participants (49.0%), with ages ranging from 18 to 30 years (M = 20.89, SD = 2.06). Most participants were pursuing their bachelor's degrees (n = 287, 74.7%), with the rest pursuing their master's degrees (n = 84, 21.9%) or MPhil/PhD degrees (n = 13, 3.4%). The sample was of 50.0% students of University of the public and 50.0% of students of the private University, which is in line with the balanced sampling approach. Regarding year of study, 28.4% were in their first year, 31.3% in their second year, 24.2% in their third year and 16.1% in their fourth year and above. The distribution of household income showed that 29.7 percent of the participants belonged to households with monthly incomes of less than PKR 50,000, 44.5 percent to households with incomes ranging between PKR 50,000-150,000 and 25.8 percent to households with incomes of more than PKR 150,000. This income distribution indicated the anticipated socioeconomic heterogeneity of both public and private university students in Islamabad with private university students much more likely to report greater household incomes (chi-square(2) = 41.67, p <.001).

Variable	Category	Frequency (n)	Percentage (%)
Gender	Female	196	51.0%
	Male	188	49.0%
Age	Range	18–30 years	—
	Mean (M)	20.89	—
	Standard Deviation (SD)	2.06	—
Education Level	Bachelor's	287	74.7%
	Master's	84	21.9%
	MPhil/PhD	13	3.4%
University Type	Public	192	50.0%
	Private	192	50.0%
Year of Study	1st Year	—	28.4%
	2nd Year	—	31.3%
	3rd Year	—	24.2%
	4th Year or Above	—	16.1%
Household Income	Below PKR 50,000	—	29.7%
	PKR 50,000 – 150,000	—	44.5%
	Above PKR 150,000	—	25.8%

AI Platform Usage and Digital Engagement Patterns

Descriptive analysis of digital platform usage revealed that Instagram was the most widely used AI-powered platform among participants (n = 301, 78.4%), followed by YouTube (n = 293, 76.3%), TikTok (n = 271, 70.6%), Facebook (n = 218, 56.8%), and Twitter/X (n = 167, 43.5%). The average usage of AI-powered platforms was 3.41 (SD = 1.12). The average daily time spent on social media was 4.23 (SD = 2.07) and there was no significant gender difference in total daily time spent on social media (t(382) = 1.43, p = .153). Nonetheless, the level of use was much higher among the students of the private university compared to students of the public university (M = 4.71 vs. M = 3.75; t(382) = 4.52, p <.001). A significant percentage of respondents (71.4) thought that the content they saw on social media was personalized to their interests, and only 34.1% thought that they knew how the platforms decide what content to show them, meaning that there was a high level of perceived personalization and low level of knowledge of algorithmic transparency.

Platform	Frequency (n)	Percentage (%)
Instagram	301	78.4%
YouTube	293	76.3%
TikTok	271	70.6%
Facebook	218	56.8%
Twitter/X	167	43.5%

Reliability and Measurement Validity

All measurement scales had strong internal consistency as shown by a reliability analysis. Rosenberg Self-Esteem Scale showed high levels of reliability (Cronbachs alpha =.88) which is also in line with other psychometric analyses of this scale that have been conducted on the international sample. The AI-Based Content filtering Perception Scale proved to be reliable (alpha =.83) and the Digital literacy Scale proved to be reliable (alpha =.87). All the retained items showed item-total correlations that were above the .35 significance level and none of the items had corrective alpha values that would enhance the scale reliability when they are deleted, which confirms all items added their own significance to their corresponding composite scores. All constructs had composite reliability values that were above .80 (RSES CR =.91, AI Filtering CR =.86, Digital Literacy CR =.89) which further supports measurement reliability on top of the Cronbach alpha.

The three-factor model of measurement in AMOS 26 was tested using confirmatory factor analysis. Overall model fit was good: chi-square(df = 289) = 521.7, p < .001; CFI = .961; TLI = .954; RMSEA = .047 (90% CI: .041-.054); SRMR = .059. The sum of all standardized loading of the factors was all above .50 with most of them above .65, which suggests satisfactory convergent validity. All three constructs had an average variance extracted above the .50 criteria (RSES AVE =.57, AI Filtering AVE =.52, Digital literacy AVE =.54). 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. Discriminant validity was proven with all the HTMT ratios having lower values than the conservative .85 (maximum HTMT =.74, between AI Filtering and Self-Esteem). According to a single-factor test used by Harman, 22.3% of the total variance was explained by one factor, which is less than the 25% concern level, and the common latent factor method used in AMOS revealed that the common method bias was associated with a non-significant additional contribution to model fit, all indicating that common method variance was not a significant threat to the validity of the findings.

Scale	Cronbach's Alpha
Rosenberg Self-Esteem Scale (RSES)	.88
AI Content Filtering Perception	.83
Digital Literacy Scale	.87

Descriptive Statistics and Correlation Analysis

The total mean score of RSES of the entire sample was 29.47 (SD = 5.84), which is a moderate value of self-esteem in accordance with published norms of Pakistani university student groups (Akhtar and Mukhtar, 2015). Female students reported significantly lower mean self-esteem than male students (M = 28.61 vs. M = 30.37; t(382) = 3.02, p = .003, d = .31). The mean self-esteem of the students of a public university was slightly higher than that of students in the private university, but this difference was not significant when gender and year of study were taken into consideration (M = 29.91 vs. M = 29.03; t(382) = 1.49, p =.137). The one-way ANOVA showed that there was significant difference among digital literacy scores across type of university (F(1, 382) = 12.47, p < .001), with students in private university reporting significantly higher digital literacy (M = 64.31 vs. M = 61.28 out of 90), possibly due to increased access to technological-rich learning environments. The average AI Filtering Perception was 31.74 (SD = 6.12) out of the potential 50, with higher scores representing the perceived intensity and effect of AI-based content filtering.

Variable	Mean (M)	SD
Self-Esteem (RSES)	29.47	5.84
AI Filtering Perception	31.74	6.12
Digital Literacy (Private)	64.31	—

Digital Literacy (Public)	61.28	—

The correlation analysis conducted by Pearson showed that there was a significant negative relationship between AI-based content filtering perception and self-esteem (r = -.34, p <.001), meaning that a higher perception of AI-based content filtering intensity and influence did decrease self-esteem in students. Self-esteem was positively related to digital literacy (r = +.28, p =. 001) so that the higher the digital literacy the higher the self-esteem. Perception of AI-based content filtering was negatively linked with digital literacy (r = -.22, p <.001) indicating that more digitally literate students perceived AI-based content filtering as less severe or less negatively effective. The perceived correlation between AI filtering and digital literacy (r = -.22) was low enough to disregard multicollinearity issues in the structural model, which was also supported by the variance inflation factors (VIF = 1.231.87) in the initial regression model.

Variables	**r**	**p-value**
AI Filtering → Self-Esteem	-.34	< .001
Digital Literacy → Self-Esteem	.28	< .001
Digital Literacy → AI Filtering	-.22	< .001

Structural Equation Modeling: Direct Effects

The covariance based model in AMOS 26 was robustly tested by testing the structural model with maximum likelihood estimation by using SmartPLS 4.0. In the baseline model, where the interaction term is omitted, AI-based content filtering perception showed a significant negative direct effect on the self-esteem (beta = -.31, t = 5.47, p < .001, 95% CI: -.42 to -.20), which confirms Hypothesis 1. Digital literacy had a significant impact, and a positive effect on self-esteem (beta =.24, t= 4.13, p=.001, 95% CI:.13 to.36) meaning that higher digital literacy was directly related to higher self-esteem even after taking into account AI filtering perception. Control variables as covariates (demographic) revealed that gender had a significant impact on predicting self-esteem (beta = -.16, p =. 004) with female students having lower self-esteem, whereas the control variables of university type (beta = -.08, p =.142) and year of study (beta =. 06, p =.214) did not have a significant The structural model at the baseline showed good fit: CFI =.958; TLI =.948; RMSEA =.049; SRMR =.063.

Path	**Beta (β)**	**t-value**	**p-value**
AI Filtering → Self-Esteem	-.31	5.47	< .001
Digital Literacy → Self-Esteem	.24	4.13	< .001
Gender → Self-Esteem	-.16	—	.004
University Type → Self-Esteem	-.08	—	.142
Year of Study → Self-Esteem	.06	—	.214

Moderation Analysis: The Buffering Role of Digital Literacy

The SmartPLS 4.0 was used to perform moderation analysis in the product indicator approach to form the AI Filtering x Digital Literacy interaction term, where all the indicators of the constituent constructs were mean-centered before the computation of the products to minimize the effects of multicollinearity. Bootstrapping, using 5,000 samples, produced bias-corrected confidence intervals on all the path coefficients and interaction term. The AI Filt 2 × Digital Literacy interaction term was found to have a significant positive path coefficient with self-esteem (beta =.26, t = 4.09, p =.001, 95% CI:.13 to.38), thus satisfying Hypothesis 2 and showing that digital literacy significantly mediated the negative association between AI-based content filtering perception and self-esteem.

Simple slope analysis was used to investigate the nature of the moderation effect to estimate the relationship between AI filtering perception and self-esteem at a single standard deviation above and below the mean of digital literacy. At the high digital literacy level (+1 SD) the negative correlation between AI filtering perception and self-esteem was much smaller and insignificant (simple slope = -.09, t = 1.41, p = .159), meaning that digitally literate students were practically insulated against the self-esteem-destroying effect of AI-based content filtering. The negative correlation between self-esteem and perception of AI-based content filtering was stronger and significantly significant at lower levels of digital literacy (-1 SD) when students with lower digital literacy were more susceptible to the self-esteem-reducing impact of perceived AI-based content filtering. The theoretical propositions based on the digital literacy scholarship and this classic moderating pattern of buffering was in line with the theoretical propositions and offered the clear support of the moderating effect of digital literacy on the AI filtering-self esteem relationship.

The total model that accommodates AI filtering perception, digital literacy, the interaction term between the two, and demographic controls explained the variation in self-esteem by R 2 =.31- meaning that the model accommodated 31 percent of the variance in self-esteem, which is substantial as the effect sizes of most studies in psychology investigating the impact of social media and self-assessments tend to be lower. The calculated effect sizes of the moderation interaction based on Cohen (1988) f 2 showed a small-to-medium effect (f 2 = .09), which is deemed practically significant in psychological moderation studies, with the magnitude of interaction effects generally being lower than that of main effects. The AMOS covariance-based SEM robustness test generated similar coefficients of path and verified the significance of the moderation interaction

(beta =.23, p =.002), which further supported the reliability of the moderation results obtained using other methods of analysis.

Supplementary Analyses

The main AI filtering to self-esteem relationship was moderated by gender in multi-group SEM analysis: females were significantly more strongly negatively influenced by the AI filtering perception on self-esteem (beta = -.40, p <.001) than males (beta = -.22, p =.007), and the difference in chi-square test between them was significant (chi-square(1) difference = Digital literacy revealed a greater buffering effect in female students compared to male students, which was in line with general trends in the digital literacy and gender literature indicating that digital literacy skills might be especially protective of populations at increased risk of self-esteem harm due to the algorithmic curation of social comparison spaces. The structural model difference between the students of public and private universities did not appear statistically significant once the level of digital literacy was taken into account, which indicated that the pattern of the moderation was similar in the institutional settings.

DISCUSSION

The results of the current research offer strong empirical data supporting that AI-based content filtering perception is strongly and negatively correlated with self-esteem in university students in Islamabad, Pakistan, and that digital literacy modulates this correlation, with high levels of digital literacy playing an important role in psychological buffering against the adverse self-esteem effects of AI-filtered content settings. These findings are consistent with and generalizable to the theoretical frameworks which were used in the present work, including social comparison theory, self-determination theory, and Uses and Gratifications perspectives, which all postulate that the psychological influence of algorithmically curated content environments will depend on the cognitive and competency resources that individual users possess when engaging in digital interaction.

The large direct negative impact of AI filtering perception on self-esteem (beta = -.31) is in line with the results of previous studies that suggest that exposure to algorithmically selected social comparison information on social network sites correlates with negative self-appraisal (Vogel et al., 2014; Fardouly et al., 2015). The current research builds on this body of literature by defining AI-based content filtering as a specific variable of perceptions of intensity of personalization, transparency, informational control, and social comparison facilitation instead of using aggregate social media use or platform-specific measures of exposure. This operationalization permits attributing the effects of self-esteem more accurately to the algorithmic structure of the content delivery mechanism, as opposed to the overall properties of social media usage, and is a methodological contribution to a developing area of interest. The highly significant buffering impact of the digital-literacy (interaction beta =.26) and the simple slope analysis showing that almost all AI filtering levels produce practically non-existent effects on self-esteem support the protective impact of digital literacy ability in AI-mediated self-evaluative processes. The result that female students reported greater negative impacts of AI filtering on self-esteem and greater buffering impact of digital literacy is in line with the cultural background of this study and with the existing studies that claimed that gender is a modifier of social media psychological outcomes in South Asian populations (Zaman et al., 2021).

CONCLUSION AND RECOMMENDATIONS

This research found that AI-based content filtering perception was strongly and significantly related to self-esteem among university students in Islamabad, Pakistan, and that digital literacy acted as a significant moderator of this association, which lessened the negative effects of this association in higher-digital-literacy competency students. These results are added to the expanding interdisciplinary research on AI-mediated psychological effects and offer the first quantitative support of such a pattern of moderation in a higher education setting in Pakistan.

The following are the recommendations that are furthered on the basis of the empirical results. To start with, digital literacy curricula need to be incorporated, in both mandatory introductory subjects, in all Pakistani universities, with particular content units covering algorithm awareness, content filtering algorithms, social comparison psychology in algorithmically mediated spaces, and self-regulated approaches to deliberate digital interaction. Due to the more significant protective role of digital literacy in female students, the need to develop gender-responsive digital literacy programs is justified. Second, AI-based content filtering perception must be introduced as an important predictor of self-esteem outcomes in addition to other risk factors into the motivational package of routine student mental health screening within university counseling services. Third, Pakistan Telecommunication Authority and the Higher Education Commission of Pakistan ought to establish policy frameworks that will ensure social media companies active in Pakistan are more algorithmically transparent to their end-users, allowing them to make more knowledgeable decisions regarding their content filtering settings and minimize the psychological costs of their perceived algorithmic opaqueness. Fourth, design and developers of AI platforms must integrate user well-being metrics and self-esteem impact measurements into algorithm evaluation models, focusing on content diversity and user autonomy and optimization of

engagement in the design of recommendation systems. Fifth, longitudinal designs should be used in future studies to determine the directionality of relationships between AI filtering perception, digital literacy, and self-esteem over time, determine which content dimensions of algorithmically-mediated environments most and least strongly predict self-esteem outcomes, and determine which digital literacy intervention programs could be used as a method of improving self-esteem outcomes in AI-saturated educational environments.

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