Exploration of Digital Health Technologies

Open Exploration

Open Access Original Article

Behavioral signature of the Algorithmic Self in AI-filtered digital environments

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Academic Editor: Subho Chakrabarti, Postgraduate Institute of Medical Education and Research (PGIMER), India
Received: January 25, 2026 **Accepted:** April 30, 2026 **Published:** June 16, 2026

Cite this article: Hammad M, Shakoor K. Behavioral signature of the Algorithmic Self in AI-filtered digital environments. Explor Digit Health Technol. 2026;4:101196. https://doi.org/10.37349/edht.2026.101196

Abstract

Aim: To examine the behavioral signature of the "Algorithmic Self," characterizing how users adapt their identity and behaviors in response to algorithmic reinforcement among active digital media users in Pakistan.

Methods: A cross-sectional quantitative design was employed with 422 adults aged 18–45 years across five major cities. Participants completed a structured online questionnaire capturing demographic data, digital usage patterns, the Algorithmic Exposure Score (AES), and Algorithmic Self Behavioral Signature Scale (ASBSS). Validated instruments assessed social comparison, Fear of Missing Out (FoMO), self-esteem, and digital stress. Data were analyzed using descriptive statistics, Pearson correlations, and multiple linear regression in SPSS version 26, with significance set at $p < 0.05$.

Results: Participants demonstrated moderate-to-high levels of Algorithmic Self formation, with 39.8% classified in the high category. Higher daily screen time, greater platform diversity, stronger algorithmic trust, and elevated social comparison were associated with higher Algorithmic Self Scores. In multiple linear regression analysis, daily screen time ($\beta = 0.34$), social comparison ($\beta = 0.31$), algorithmic trust ($\beta = 0.29$), and algorithmic exposure ($\beta = 0.28$) emerged as significant predictors of Algorithmic Self formation, while FoMO was not a significant predictor ($\beta = 0.11$, $p = 0.09$). The final model explained 56% of the variance in Algorithmic Self formation ($R^2 = 0.56$, adjusted $R^2 = 0.54$, $p < 0.001$).

Conclusions: AI-driven digital environments are associated with self-presentation, identity adaptation, and behavioral regulation among Pakistani users. These findings highlight the importance of enhancing digital literacy, improving awareness of algorithmic influence, and further investigating the psychological and societal implications of Algorithmic Self formation in digitally mediated environments.

Keywords

Algorithmic Self, AI-filtered reality, behavioral signatures, human-AI interaction, digital identity

Introduction

Artificial intelligence (AI) is rapidly integrating into digital environments and has fundamentally reshaped how individuals perceive, evaluate, and present themselves. AI-driven algorithms curate digital content, design personalized newsfeeds, optimize user engagement, and reinforce behavioral patterns based on predictive analytics [1]. In Pakistan, internet penetration has exceeded 50%, with over 120 million users actively engaging with social media platforms, highlighting the scale of algorithmically mediated digital exposure [2]. This widespread integration has intensified human–algorithm interaction, making algorithmic systems central to everyday digital behavior and self-presentation.

Increasingly, AI-filtered environments create feedback loops in which individuals adjust their behavior, preferences, and identity presentation in response to algorithmic reinforcement, a phenomenon conceptualized in this study as the “Algorithmic Self.” Within this conceptualization, the Algorithmic Exposure Score (AES) is introduced as a composite indicator that quantifies individuals’ interaction with algorithmically curated environments by integrating frequency, duration, and diversity of digital platform engagement. Higher AES values reflect greater immersion in algorithmically personalized content ecosystems and increased behavioral susceptibility to algorithmic reinforcement. Research indicates that algorithmic curation shape’s digital identity, alters social comparison processes, and influences emotional and cognitive outcomes [3, 4]. These changes often occur subtly and outside conscious awareness, potentially affecting autonomy, decision-making, and psychological well-being. Emerging evidence further links algorithmic systems to broader societal outcomes, including political polarization, misinformation dissemination, and rising mental health concerns associated with excessive digital engagement [5, 6].

As AI becomes increasingly embedded in social media platforms, recommendation engines, educational technologies, and workplace systems, understanding its behavioral implications has become increasingly urgent [6]. Although research on algorithmic bias, digital nudging, and personalized content effects has expanded, the existing literature remains fragmented and largely domain-specific, focusing primarily on isolated outcomes such as consumer behavior, attention modulation, or political polarization [4–7]. This fragmented approach limits a comprehensive understanding of how algorithmic systems collectively shape identity formation, self-perception, and interpersonal behavior. Recent interdisciplinary advances in human-AI interaction, including AI-based mental health prediction, human-robot communication frameworks, and AI-enabled telemedicine systems; further highlight the pervasive influence of intelligent systems on human cognition and behavior, reinforcing the need for an integrated behavioral framework [8].

A further limitation of existing literature is its strong Western-centric orientation, which restricts the generalizability of findings across diverse socio-cultural contexts. In South Asia, and particularly Pakistan, digital behavior is shaped by unique cultural, socio-economic, and technological infrastructures that remain underrepresented in empirical research. Pakistan’s rapidly expanding digital ecosystem and high engagement with algorithmically driven platforms provide a critical context for examining how individuals internalize algorithmic cues and adapt their behavior accordingly. Despite this relevance, no prior study has systematically operationalized and empirically examined the behavioral, cognitive, and emotional dimensions of the Algorithmic Self in this population [5, 8].

Addressing this gap is essential for understanding how AI-mediated environments influence autonomy, identity formation, and behavioral regulation. The Algorithmic Self has important implications for mental health, digital literacy, political participation, and online professionalism [9]. Within algorithmically structured environments, individuals may increasingly adapt their behavior to optimize engagement metrics rather than express authentic identity, reflecting a shift toward algorithmically reinforced self-presentation**.** Although prior studies have demonstrated associations between algorithmic exposure and psychological outcomes, the construct of the Algorithmic Self remains theoretically underdeveloped and lacks standardized empirical operationalization [10].

In this context, generating evidence from Pakistan contributes to global digital behavioral science by providing culturally contextualized insights that address prevailing Western-centric biases in AI ethics and behavioral models [11]. Additionally, there is limited empirical work examining how algorithmic exposure interacts with psychological factors to produce measurable behavioral adaptations in non-Western digital environments. Accordingly, the primary objective of this study is to examine the behavioral signature of the Algorithmic Self and its association with algorithmic exposure and psychological factors among digital media users in Pakistan.

The present study makes the following key contributions:

- Develops and operationalizes the Algorithmic Self through a measurable behavioral framework [Algorithmic Self Behavioral Signature Scale (ASBSS)].
- Provides empirical evidence linking algorithmic exposure, psychological traits, and behavioral adaptation in a non-Western population.
- Identifies key predictors of algorithmically influenced self-presentation, including screen time, social comparison, and algorithmic trust.
- Advances theoretical understanding of human-AI interaction and digital identity formation.

This paper is structured as follows: Section 2 presents the Materials and methods, including study design and measurement tools. Section 3 reports the Results. Section 4 discusses the findings, implications, and future directions.

Materials and methods

A cross-sectional quantitative research design was employed to investigate the behavioral signature of the "Algorithmic Self" among active digital media users in Pakistan. The study was conducted across five major urban centers (Karachi, Lahore, Islamabad, Peshawar, and Quetta), selected due to high digital connectivity, socio-cultural diversity, and substantial engagement with AI-driven platforms. The target population comprised adults aged 18–45 years who engaged with at least one algorithm-based social media platform (such as TikTok, Instagram, YouTube, or Facebook) for a minimum of one hour daily, ensuring adequate exposure to algorithmically curated content.

A total of 422 participants were included in the study. Sample size was calculated using the standard formula for cross-sectional studies: $n = Z^2p(1 - p)/d^2$, where $Z = 1.96$, $p = 0.50$, and $d = 0.05$. The minimum required sample size was 384, which was increased by 10% to account for incomplete responses [12]. A multistage sampling approach was used, consisting of cluster selection of cities followed by non-probability convenience sampling within each cluster due to the online nature of data collection. Ethical approval was obtained from the Institutional Review Board of Lady Reading Hospital, Medical Teaching Institution (Ref no: 708/LRH/MTI). Ethical safeguards included anonymization of responses, secure data storage, and voluntary participation with the right to withdraw at any time.

Data were collected using a structured, self-administered online questionnaire disseminated through multiple digital channels, including WhatsApp groups, university portals, email lists, and social media platforms. This approach enhanced accessibility and facilitated recruitment of a diverse sample; however, potential selection bias toward digitally active users was acknowledged. The questionnaire consisted of demographic items (age, gender, education, and employment), indicators of digital usage (screen time, platform preferences, and purpose of use), AES, and ASBSS. The AES was developed specifically for this study to quantify the degree of behavioral exposure to algorithmically curated platforms. The conceptual foundation of the measure is informed by existing literature on algorithmic systems, digital inequalities, and user interaction with algorithm-driven platforms [13]. Unlike measures of algorithm awareness, which assess users' knowledge or understanding of algorithmic processes, AES operationalizes the extent of actual exposure to algorithmically mediated content and platform structures. The score was constructed as a composite index incorporating self-reported frequency of use, duration of engagement, and diversity of interaction across major algorithm-driven platforms. Higher AES values indicate greater cumulative exposure to environments in which algorithms influence content visibility, information consumption, and online engagement patterns. The measure was designed to capture behavioral exposure to algorithmic curation rather than users' cognitive perceptions or awareness of algorithmic mechanisms.

To assess behavioral adaptation to perceived algorithmic influence, the ASBSS was developed through a systematic multi-stage process. Its theoretical foundation is informed by the conditional logic framework proposed by Bucher (2018), particularly the "if...then" mechanisms through which algorithms anticipate, structure, and regulate user actions [14]. Building upon this theoretical foundation, the ASBSS was designed to operationalize the behavioral signatures that emerge when individuals modify their online activities in response to perceived algorithmic expectations and visibility dynamics. Scale development followed a rigorous multi-stage process. Initially, an extensive review of the literature on digital behavior, algorithmic influence, and online self-presentation was conducted to generate a preliminary item pool. Subsequently, items were refined based on conceptual relevance, clarity, and alignment with the underlying theoretical framework. The ASBSS consisted of 28 items distributed across the five domains, including algorithm-optimized self-presentation (8 items), content modification for visibility (6 items), engagement maximization behaviors (5 items), emotional regulation based on algorithm feedback (4 items), and identity flexibility toward algorithms (5 items). All items were rated on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Domain scores were summed to generate a total raw score ranging from 28 to 140, which was subsequently normalized to a 0–100 scale using the formula: [(observed score − minimum possible score)/(maximum possible score − minimum possible score)] × 100. Higher scores indicated greater behavioral adaptation to perceived algorithmic influence and algorithmically mediated self-presentation. For descriptive analyses, normalized scores were categorized as low (0–49), moderate (50–69), and high (70–100) levels of Algorithmic Self formation. Content validity was assessed by a panel of four experts in digital behavior, public health, and psychometrics who reviewed the items for relevance, clarity, and representativeness. Feedback from the expert panel was incorporated into the refinement of the final item set. A pilot study involving 30 participants was then undertaken to assess item comprehensibility and preliminary reliability. The resulting scale demonstrated satisfactory internal consistency (Cronbach's $\alpha = 0.82$). However, construct validity (e.g., exploratory and confirmatory factor analysis) was not yet established and will be examined in future studies using larger and more diverse samples. Moreover, well-established validated psychological scales measuring Fear of Missing Out (FoMO) [15], social comparison [16], self-esteem [17], and digital stress [18] were included to assess psychological constructs relevant to algorithmic behavior.

Data were analyzed using SPSS version 26. Descriptive statistics, including means and standard deviations for continuous variables and frequencies and percentages for categorical variables, were calculated to summarize participants' demographic characteristics, digital usage behaviors, algorithmic exposure, psychological constructs, and behavioral signatures of the Algorithmic Self. All descriptive results were interpreted within the study sample without population-level generalization.

For inferential analysis, Pearson's correlation coefficients were computed to examine associations between continuous variables, including Algorithmic Self Scores (ASS), algorithmic exposure, screen time, platform use, social comparison, algorithmic trust, and FoMO. Statistical significance for correlation analysis was interpreted using a conservative threshold, with most correlations meeting $p < 0.001$, while *p*-values above this threshold were reported as exact values. To identify predictors of Algorithmic Self formation, multiple linear regression analysis was conducted. ASS was entered as the dependent variable. Daily screen time (< 4 hours vs ≥ 4 hours), platform count (≤ 2 vs ≥ 3 platforms), algorithmic trust (low vs high), and social comparison (low vs high) were entered as categorical predictors and dummy-coded using the lower category as the reference group. AES and FoMO were included as continuous predictors. Standardized beta coefficients (β), 95% confidence intervals (CIs), and *p*-values were reported. Model assumptions, including linearity, homoscedasticity, multicollinearity, and normality of residuals, were assessed following established statistical guidelines [19, 20]. Model fit was evaluated using R^2 and adjusted R^2. Statistical significance was set at $p < 0.05$.

Results

Sample was nearly balanced by gender, with 52.1% male (n = 220) and 47.9% female (n = 202). The majority of participants were young adults aged 18–25 years (41.0%), followed by those aged 26–35 years (37.2%) and 36–45 years (21.8%). In terms of education, most participants held an undergraduate degree (41.7%), with 33.9% having graduate-level education, 13.0% postgraduate, and 11.4% intermediate-level education. Regarding employment, 45.5% were students, 37.4% employed, 9.0% self-employed, and 8.1% unemployed. Monthly income was distributed evenly, with 36.0% earning 180–360 USD, 36.0% earning above > 360 USD, and 28.0% earning below < 180 USD.

Digital usage patterns indicated substantial engagement: 14.0% reported less than 2 hours, 22.5% reported 2–4 hours, 36.5% reported 4–6 hours, and 27.0% reported more than 6 hours of daily screen time. Smartphones were the primary device for 84.4% of participants, while 15.6% used laptops or desktops.

Social media engagement showed a clear distribution pattern, with 24.4% using 1–2 platforms, 47.6% using 3–4 platforms, and 28.0% using 5+ platforms. YouTube emerged as the most frequently used platform (36.0%), followed by TikTok (26.5%), Instagram (23.2%), and Facebook (14.2%). The primary purpose of social media usage was entertainment (50.5%), followed by education (23.5%), work-related purposes (18.5%), and socializing (7.5%) (Table 1).

Table 1. Demographic and digital usage characteristics of participants (*N* = 422).

Variable	Categories	*n*	%
Gender	Male	220	52.1
	Female	202	47.9
Age group (years)	18–25	173	41.0
	26–35	157	37.2
	36–45	92	21.8
Education level	Intermediate	48	11.4
	Undergraduate	176	41.7
	Graduate	143	33.9
	Postgraduate	55	13.0
Employment status	Student	192	45.5
	Employed	158	37.4
	Self-employed	38	9.0
	Unemployed	34	8.1
Monthly income (USD)	< 180	118	28.0
	180–360	152	36.0
	> 360	152	36.0
Daily screen time	< 2 hours	59	14.0
	2–4 hours	95	22.5
	4–6 hours	154	36.5
	> 6 hours	114	27.0
Primary device	Smartphone	356	84.4
	Laptop/Desktop	66	15.6
Social media platforms used	1–2	103	24.4
	3–4	201	47.6
	≥ 5	118	28.0
Most used platform	YouTube	152	36.0
	TikTok	112	26.5
	Instagram	98	23.2
	Facebook	60	14.2

Table 1. Demographic and digital usage characteristics of participants (*N* = 422). (*continued*)

Variable	Categories	*n*	%
Usage purpose	Entertainment	213	50.5
	Education	99	23.5
	Work	78	18.5
	Socializing	32	7.5

Table 2 presents the cross-tabulation of age group and education level by gender among the study participants. The distribution of age groups was relatively balanced across male and female participants. In the 18–25 years category, males accounted for 43.2% (*n* = 95) and females for 38.6% (*n* = 78). In the 26–35 years group, the proportions were comparable between males (36.8%, *n* = 81) and females (37.6%, *n* = 76), while in the 36–45 years category, females (23.8%, *n* = 48) were slightly higher than males (20.0%, *n* = 44), indicating no marked gender-based age clustering.

Table 2. Cross-tabulation of age group, gender, and education level (*N* = 422).

Variable	Categories	Male *n* (%)	Female *n* (%)	Total
Age group (years)	18–25	95 (43.2)	78 (38.6)	173
	26–35	81 (36.8)	76 (37.6)	157
	36–45	44 (20.0)	48 (23.8)	92
Education level	Intermediate	28 (12.7)	20 (9.9)	48
	Undergraduate	90 (40.9)	86 (42.6)	176
	Graduate	72 (32.7)	71 (35.1)	143
	Postgraduate	30 (13.7)	25 (12.4)	55

A similar pattern was observed in educational attainment. The majority of participants in both genders were concentrated at the undergraduate level (males: 40.9%, females: 42.6%), followed by graduate education (males: 32.7%, females: 35.1%). Postgraduate qualification was slightly higher among males (13.7%) compared to females (12.4%), while the proportion of participants with intermediate education was relatively low in both groups (males: 12.7%, females: 9.9%). Overall, the findings indicate a broadly comparable demographic distribution between male and female participants across both age and education strata, with no substantial gender-based disparities observed.

Table 3 presents participants' algorithmic exposure metrics, psychological characteristics, and scale properties. The mean AES was 68.4 (SD = 11.5), indicating moderate-to-high engagement with algorithmically curated digital environments among participants. AES represents a composite index reflecting frequency, duration, and diversity of engagement across algorithm-driven platforms, with higher scores indicating greater exposure to algorithmic content ecosystems. Algorithmic trust was categorized into low, moderate, and high levels based on a composite Likert-scale measure assessing perceived reliability, accuracy, and usefulness of algorithmic recommendations. The distribution showed 18.0% low trust, 52.0% moderate trust, and 30.0% high trust, reflecting heterogeneous levels of confidence in algorithmic systems.

Table 3. Algorithmic exposure, psychological characteristics, and scale properties.

Variable	Mean ± SD/*n* (%)	Scale range
Algorithmic Exposure Score (AES)	68.4 ± 11.5	0–100
Algorithmic trust		0–100
Low	76 (18.0%)	0–33
Moderate	219 (52.0%)	34–66
High	127 (30.0%)	67–100
Perceived algorithmic control	3.8 ± 0.7	1–5 Likert

Table 3. Algorithmic exposure, psychological characteristics, and scale properties. (*continued*)

Variable	Mean ± SD/*n* (%)	Scale range
Personalization awareness	3.5 ± 0.8	1–5 Likert
Algorithm-influenced decisions	3.9 ± 0.6	1–5 Likert
Social comparison tendency	3.41 ± 0.72	1–5 Likert
Self-esteem	27.8 ± 4.3	10–40
Need for social approval	30.1 ± 6.2	10–50
Fear of Missing Out (FoMO)	32.5 ± 7.1	10–50
Digital stress	18.3 ± 5.6	8–40
ASBSS reliability (Cronbach's α)	0.82	–

Participants reported moderate perceived algorithmic control (M = 3.8, SD = 0.7), personalization awareness (M = 3.5, SD = 0.8), and algorithm-influenced decision-making (M = 3.9, SD = 0.6), suggesting a noticeable behavioral integration of algorithmic systems in daily digital activity. Psychological characteristics indicated a moderate tendency toward social comparison (M = 3.41, SD = 0.72), relatively high self-esteem (M = 27.8, SD = 4.3), and elevated need for social approval (M = 30.1, SD = 6.2). Participants also demonstrated moderate levels of FoMO (M = 32.5, SD = 7.1) and digital stress (M = 18.3, SD = 5.6), highlighting the psychological influence of algorithmically mediated digital environments. The ASBSS demonstrated acceptable internal consistency (Cronbach's α = 0.82), indicating satisfactory reliability for exploratory research use.

Table 4 presents the behavioral signature of the Algorithmic Self (ASBSS domains) along with the associated correlation analysis. Participants demonstrated varying levels of algorithmically influenced behaviors across the five ASBSS domains. The highest mean score was observed in algorithm-optimized self-presentation (M = 28.7, SD = 5.3), indicating frequent adjustment of self-presentation strategies to enhance algorithmic visibility. This was followed by content modification for visibility (M = 21.4, SD = 4.8) and engagement maximization behaviors (M = 18.2, SD = 4.1), reflecting active efforts to increase digital reach and interaction. Moderate levels were observed for emotional regulation based on algorithm feedback (M = 14.9, SD = 3.2) and identity flexibility toward algorithms (M = 17.5, SD = 3.9), suggesting adaptive emotional and identity-related responses to algorithmic cues.

Table 4. Behavioral signature of the Algorithmic Self (ASBSS domains), classification of ASS, and Pearson correlation analysis with ASS.

Variable	Mean ± SD/*n* (%)	Scale range
Algorithm-optimized self-presentation	28.7 ± 5.3	8–40
Content modification for visibility	21.4 ± 4.8	6–30
Engagement maximization behaviors	18.2 ± 4.1	5–25
Emotional regulation based on algorithm feedback	14.9 ± 3.2	4–20
Identity flexibility toward algorithms	17.5 ± 3.9	5–25
Overall ASS classification		
Low	78 (18.5%)	0–49
Moderate	176 (41.7%)	50–69
High	168 (39.8%)	70–100
Pearson Correlation Analysis	***r* [95% CI]**	***p*-value**
Algorithmic Exposure Score (AES)	0.62 [0.55–0.68]	< 0.001
Daily screen time	0.48 [0.40–0.55]	< 0.001
Social comparison	0.55 [0.48–0.61]	< 0.001
Algorithmic trust	0.51 [0.43–0.58]	< 0.001
Platform count	0.39 [0.31–0.46]	< 0.001
FoMO	0.24 [0.14–0.33]	0.002
Self-esteem	–0.41 [–0.49 – –0.32]	< 0.001

ASBSS total score normalized to a 0–100 scale for interpretability. Pearson correlation coefficients represent bivariate associations between ASS and continuous predictor variables.

Regarding overall classification, 18.5% of participants were categorized as low, 41.7% as moderate, and 39.8% as high in ASS, indicating that a substantial proportion of users exhibit strong behavioral adaptation to algorithmically curated environments. Correlation analysis showed that ASS were significantly associated with AES (r = 0.62 [0.55–0.68], p < 0.001), social comparison (r = 0.55 [0.48–0.61], p < 0.001), algorithmic trust (r = 0.51 [0.43–0.58], p < 0.001), daily screen time (r = 0.48 [0.40–0.55], p < 0.001), platform count (r = 0.39 [0.31–0.46], p < 0.001), and FoMO (r = 0.24 [0.14–0.33], p = 0.002), self-esteem (r = –0.41 [–0.49 – –0.32], p < 0.001), indicating that both digital behavior and psychological factors are significantly related to Algorithmic Self formation.

Table 5 presents the associations and predictors of ASS formation among participants. Higher daily screen time (≥ 4 hours) was associated with significantly higher ASS scores (M = 72.9, SD = 7.4) compared to lower screen time (< 4 hours; M = 63.8, SD = 9.1), with a strong positive predictive effect (β = 0.34, 95% CI = 0.18–0.51, p < 0.001). Similarly, participants using three or more social media platforms exhibited higher ASS (M = 73.1, SD = 8.0) than those using one or two platforms (M = 61.2, SD = 10.4; β = 0.21, 95% CI = 0.04–0.37, p = 0.02). Algorithmic trust and social comparison tendencies were also significant predictors of higher ASS. Participants with high algorithmic trust scored 75.6 ± 7.5 compared to 58.4 ± 8.8 for those with low trust (β = 0.29, 95% CI = 0.13–0.44, p < 0.001), while individuals with high social comparison tendencies scored 75.0 ± 8.3 versus 62.2 ± 9.4 for those with low tendencies (β = 0.31, 95% CI = 0.17–0.45, p < 0.001). AES also positively predicted ASS (β = 0.28, 95% CI = 0.14–0.42, p < 0.001). Self-esteem emerged as an independent negative predictor in the regression model (β = –0.22, 95% CI: –0.36 – –0.08, p = 0.002), whereas FoMO showed a non-significant trend (β = 0.11, 95% CI = –0.02–0.25, p = 0.09). Overall regression model demonstrated a strong fit, explaining 56% of the variance in Algorithmic Self formation (R^2 = 0.56; adjusted R^2 = 0.54; p < 0.001), indicating that digital behavior, algorithmic trust, exposure, and social comparison are robust predictors of how participants adapt their online self-presentation in algorithmically mediated environments. No evidence of multicollinearity was observed among the predictor variables, with all variance inflation factor (VIF) values below 2.5.

Table 5. Associations and predictors of algorithmic self-formation.

Variable	Categories	Mean ASS ± SD	β coefficient	95% CI	*p*-value
Daily screen time	< 4 hours	63.8 ± 9.1	0.34	0.18–0.51	< 0.001
	≥ 4 hours	72.9 ± 7.4			
Platform count	≤ 2	61.2 ± 10.4	0.21	0.04–0.37	0.02
	≥ 3	73.1 ± 8.0			
Algorithmic trust	Low	58.4 ± 8.8	0.29	0.13–0.44	< 0.001
	High	75.6 ± 7.5			
Social comparison	Low	62.2 ± 9.4	0.31	0.17–0.45	< 0.001
	High	75.0 ± 8.3			
Algorithmic Exposure Score (AES)	Continuous	-	0.28	0.14–0.42	<0.001
FoMO	Continuous	-	0.11	–0.02–0.25	0.09
Self-esteem	Continuous	-	–0.22	–0.36 – –0.08	0.002
Overall model fit	-	-	R^2 = 0.56	Adjusted R^2 = 0.54	< 0.001

Discussion

The current study investigated the behavioral signature of the “Algorithmic Self” among active digital media users in Pakistan, examining the interplay between algorithmic exposure, psychological traits, and self-presentation behaviors. Consistent with prior research on algorithmic influence, participants demonstrated moderate-to-high AES, indicating substantial engagement with AI-curated content streams [21, 22]. Higher daily screen time and greater platform diversity were associated with significantly higher ASS, as reflected in group comparisons and regression findings, suggesting that sustained digital engagement strengthens algorithmically reinforced behavioral adaptation. This pattern aligns with prior studies on social media self-presentation and personalized content consumption [23].

Psychological constructs, particularly social comparison, emerged as strong correlates and predictors of Algorithmic Self formation. Participants with higher social comparison tendencies exhibited significantly higher ASS, supporting the role of evaluative social processes in algorithmically mediated environments. This observation is consistent with existing literature suggesting that algorithmic feedback loops intensify social comparison processes and reinforce online validation-seeking behavior [24, 25]. FoMO showed a weak and statistically non-significant effect in the regression model ($\beta = 0.11$, $p = 0.09$), suggesting a limited direct predictive role in Algorithmic Self formation within this sample. However, FoMO was significantly associated with ASS at the bivariate level, indicating that its influence may be indirect or mediated through other psychological or behavioral factors.

Self-esteem demonstrated a relatively weaker and more complex relationship with Algorithmic Self formation, suggesting that while individual self-perception remains relevant, algorithmic exposure and platform-driven reinforcement patterns may partially override stable self-evaluative traits in shaping online behavioral adaptation. The behavioral signature of the Algorithmic Self was characterized by algorithm-optimized self-presentation, content modification for visibility, engagement maximization behaviors, and emotional regulation based on algorithmic feedback. These findings indicate that users both consciously and unconsciously adjust their digital behavior in response to perceived algorithmic reward structures. Within the Pakistani context, these findings are particularly significant given the high dependence on social media platforms for communication, information access, and social interaction among digitally active populations. In such environments, algorithmic systems function not only as content curation mechanisms but also as indirect gatekeepers of visibility and social validation, thereby reinforcing adaptive behavioral strategies among users. Although these findings align with emerging theoretical frameworks suggesting that algorithmic systems may contribute to the shaping of online identities, the present results extend this evidence to a non-Western, high-engagement digital context. This suggests partial cross-cultural convergence in algorithm-driven behavioral adaptation; however, further comparative studies across diverse socio-digital ecosystems are required to determine the extent of universality versus cultural specificity [6, 7].

Regression analyses demonstrated that algorithmic exposure, social comparison, screen time, and algorithmic trust were significant predictors of Algorithmic Self formation, collectively explaining a substantial proportion of variance in behavioral adaptation. These results underscore the interactive role of technological exposure and psychological predispositions in shaping digital identity formation, highlighting that online self-presentation is not merely personality-driven but is dynamically structured by algorithmic environments [5].

Several limitations should be acknowledged. First, the cross-sectional design limits causal inference, and associations should not be interpreted as directional relationships. Second, the sampling strategy and online recruitment approach may introduce selection bias by overrepresenting highly active digital users. Third, reliance on self-reported measures may introduce recall and social desirability biases; future research should incorporate objective digital trace or platform analytics data. Fourth, although validated psychological instruments were used, the newly developed ASBSS requires further psychometric validation, including factor analytic testing and cross-cultural validation, to strengthen construct validity. Finally, the focus on urban Pakistani users limits generalizability to rural and less digitally connected populations.

Despite these limitations, the study provides novel empirical evidence on how algorithmic exposure and psychological traits jointly shape self-presentation behaviors in digital environments. Key predictors, including algorithmic exposure, social comparison, platform diversity, screen time, and algorithmic trust were significantly associated with Algorithmic Self formation, indicating adaptive behavioral responses to AI-driven digital ecosystems. Based on these findings, targeted recommendations are proposed across stakeholders. For researchers, replication using longitudinal and cross-cultural designs is recommended to establish causal mechanisms. For users, digital literacy programs should emphasize awareness of algorithmic influence and promote reflective engagement with curated content. For educators, integration of digital well-being and algorithmic awareness into curricula is recommended. For institutions in public health and digital governance, structured interventions addressing algorithm-related behavioral and psychological impacts are needed. At the policy level, regulatory frameworks should prioritize algorithmic transparency, ethical AI deployment, and safeguards against excessive behavioral manipulation by recommender systems. Collectively, these measures aim to strengthen responsible AI engagement and improve understanding of identity formation in algorithmically mediated environments.

Conclusion

This study examined the behavioral signature of the Algorithmic Self among digital media users in Pakistan using a cross-sectional quantitative design. Findings indicate that algorithmic exposure is associated with higher levels of Algorithmic Self formation, with screen time, platform diversity, social comparison, and algorithmic trust emerging as significant predictors in regression analyses. Participants demonstrated moderate-to-high levels of ASS, suggesting notable algorithmically influenced identity formation in digitally active populations. The multiple regression model explained a substantial proportion of variance in Algorithmic Self formation (R^2 = 0.56), indicating meaningful combined effects of digital behavior and psychological factors. Thus, the study highlights the growing role of algorithmically mediated environments in shaping online identity expression within a non-Western context. These findings underscore the importance of strengthening digital literacy, increasing awareness of algorithmic influence, and promoting responsible and reflective engagement with AI-driven platforms.

Abbreviations

AES: Algorithmic Exposure Score

ASBSS: Algorithmic Self Behavioral Signature Scale

ASS: Algorithmic Self Scores

FoMO: Fear of Missing Out

Declarations

Acknowledgments

The authors would like to thank all participants for their time and valuable input, and the university and digital platforms that facilitated data collection.

Author contributions

MH: Conceptualization, Methodology, Investigation, Writing—original draft, Writing—review & editing, Supervision, Validation. KS: Data curation, Formal analysis, Writing—review & editing. Both authors read and approved the submitted version.

Conflicts of interest

The authors declare that they have no conflicts of interest.

Ethical approval

Ethical approval was obtained from the Institutional Research Board of Lady Reading Hospital, Medical Teaching Institution (Ref no: 708/LRH/MTI). The study was conducted in accordance with the principles of the Declaration of Helsinki (2013 revision).

Consent to participate

Informed consent to participate in the study was obtained from all participants.

Consent to publication

Informed consent to publication was obtained from relevant participants.

Availability of data and materials

The datasets generated and analyzed during the current study are available from the corresponding author on reasonable request.

Funding

Not applicable.

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