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CONSTRUCTION AND VALIDATION OF ALGORITHM ANXIETY SCALE

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Abstract
Although algorithm-driven digital environments are increasingly prevalent, they introduce emerging psychological challenges, and validated instruments for measuring algorithm-related anxiety remain limited. The purpose of this study was to create and validate the Algorithm Anxiety Scale (AAS), a multidimensional scale of emotional and cognitive reactions to algorithmic systems. A sequential mixed-method design was used. Phase 1 involved qualitative interviews with social media users to gain insights into their lived experiences of being exposed to algorithm-driven content, which informed the development of items based on both empirical themes and theory such as techno-stress theory, surveillance capitalism and uncertainty management theory. The refined scale was quantitatively validated with 254 participants (18 to 60 years) during Phase 2. The two factors, Emotional Algorithm Anxiety (EAA) and Algorithmic Control and Uncertainty Perception (ACUP), were found to be stable through exploratory factor analysis. The model demonstrated acceptable fit based on confirmatory factor analysis indices (CFI = .961, RMSEA = .061, and SRMR = .066). The results of reliability analysis showed that the overall scale had a high internal consistency of α = .902, EAA of α = .871, and ACUP of α = .781. Construct validity was determined by composite reliability and inter-factor correlations. The findings suggest that algorithm anxiety represents a measurable psychological construct with affective and cognitive components related to algorithmic systems. The AAS offers a legitimate and reliable tool for further studies on digital behavior, algorithmic influence, and psychological well-being in technology-mediated environments.

INTRODUCTION

Algorithmic Society and Computational Governance

The digital infrastructures have structurally changed in the last 20 years, with the introduction of artificial intelligence, mass data extraction and automation based on machine learning. Algorithmic systems continuously analyze users' behavior to forecast their preferences, prioritize content, and organize user exposure, now increasingly shaping communication, commerce, education and social interaction. This is a shift towards an "algorithmic society" that is defined by the presence of invisible infrastructures of automated systems that influence everyday life (Beer, 2017; Gillespie, 2018) .

Recommendation architectures are used by major platforms like TikTok, Instagram, YouTube, Facebook, and X to leverage predictive analytics and behavioral profiling to boost engagement. These systems continuously adapt to user interactions, such as clicks, watch time, search patterns, and network activity, to tailor content streams. Although efficient and relevant, they increase opacity in the decision-making process, reducing the users' transparency regarding the selection or prioritization of content.

This opacity is not only technical but also epistemic in nature. Users know that algorithmic systems influence their digital experience, but lack understanding of and ability to predict how algorithmic decisions are made. Gillespie (2018) points out that algorithms serve as "curators of public relevance," and have a more influential role on visibility and attention, but lack mechanisms of transparency and accountability. Consequently, algorithmic systems are socio-technical systems that are able to redistribute agency in digital environments in a subtle way.

Algorithmic Opacity, Surveillance Capitalism, and Psychological Exposure

Algorithmic systems have been tightly tied to surveillance capitalism, a system that constantly extracts behavioral data, which is then monetized for prediction (Zuboff, 2019). All digital interactions help to build up comprehensive behavioral profiles to fine-tune ad, engagement, and platform retention tactics.

This situation has further raised the concerns about privacy, manipulation and behavioral tracking. The idea of the "filter bubble" by Pariser (2011) illustrates the limitation of informational diversity caused by personalization, and Noble (2018) points to the social biases and asymmetries of power that are created through algorithmic classification systems. All these mechanisms lead to an increasing sense of the non-neutrality of digital environments and their mediation.

Empirical studies also demonstrate that when algorithmic predictions seem to be based on private conversations or offline behavior, the users get uncomfortable. These experiences add to an individual's sense of being monitored and psychological discomfort even if systems are not invasive but probabilistic. This perception is central in the discussions that are beginning to emerge with regard to psychological distress caused by algorithms.

From Digital Stress to Algorithm Anxiety

Research on techno-stress, internet addiction and digital fatigue have increased significantly in the last decade (Tarafdar et al., 2015). But these frameworks are not exhaustive with regards to anxiety specifically related to predictive algorithmic systems. Algorithm anxiety is a psychological phenomenon characterized by emotional unease, lack of understanding, and perceived loss of control.

Whereas general digital stress is linked to the awareness of digital systems that are opaque and have a negative impact on user experience, algorithm anxiety is linked to the awareness of digital systems that actively affect user experience, but are opaque. This produces a conflict between the sense of autonomy and the influence of the algorithm. Previous studies on social media anxiety support the notion that algorithmically designed social media environments play a major role in emotional distress, such as comparison, validation-seeking, and information overload (Vannucci et al., 2017; Cotter, 2021) .

Research also indicates that there is a strong link between social media use and anxiety mediated by the social comparison, fear of negative evaluation and psychological dependence on online validation (Feinstein et al., 2013; see also recent synthesis of digital anxiety literature). But these models still fail to consider algorithms as a psychological trigger, as they are in the background.

Algorithmic Personalization and Behavioral Reinforcement

Algorithmic systems are not just filters, they are active filters that influence the behavioral patterns by focusing on content that is emotionally engaging and attention-holding. Li and Cao (2025) show that recommender systems are systematically biased towards emotionally charged content, which tends to be more engaging and thus helps to create continuous interaction loops. Likewise, Ani et al. (2024) demonstrate that algorithmic personalization leads to less informational diversity and more repetitive exposure patterns, which can result in cognitive narrowing and emotional rigidity. The results are consistent with the general issue of epistemic variety being limited in algorithmic environments, and the increase in behavioral predictability.

Algorithms also have been identified as a way to reinforce social comparison dynamics, according to research. Upward social comparison is a strong correlate of anxiety and low self-esteem (Festinger, 1954), and this association has been replicated recently in digital environments, such as social media (e.g., Instagram, Facebook). Kim (2023) also shows that recommender systems can cause echo chambers, which can lead to a reinforcement of ideas and emotions.

Algorithm Anxiety in Social Media Ecosystems

Algorithmic anxiety is the most common context in which it occurs: social media platforms. Social media platforms like TikTok, Instagram, and YouTube use algorithms to calculate content rankings, which continually dictate its visibility. As users see these systems being more and more personal, they are more likely to feel they are intruding into their personal preferences, as Cotter (2021) states.

Empirical studies in recent years have found that algorithmically curated environments lead to greater upward social comparison and to anxiety online, as exposure to idealized imagery and social feedback structures leads to greater upward social comparison. Other studies reveal that social media use is strongly linked to anxiety, loneliness and fear of negative evaluation, especially when passive consumption of social media is involved.

Performance pressure also is added to algorithmic environments. Content creators, influencers, and regular users are now more than ever being asked to adjust their actions to the perceived algorithmic preferences, such as how often and how to post content, as well as engagement tactics. This results in behavioral adaptation, but not by human audiences, but by opaque ranking systems.

Cognitive Overload, Dependency, and Emotional Fatigue

Algorithmic systems are built to engage users, and frequently this means that users are exposed to a stream of personalized content. This results in mental fatigue and emotional burnout. Belabbes et al. (2023) and Moko et al. (2023) demonstrate that overstimulation by algorithms leads to a decrease in attentional control and increase in mental fatigue.

These are exacerbated by digital dependency. Zhan et al. (2025) show that the digital stress positively correlates with anxiety, emotional instability and problematic social media use among students. Likewise, Qin et al. (2024) state that algorithmic environments are a source of psychological burnout because of the pressure of engagement that is experienced continuously.

There have been systematic reviews that have found that long-term use of social media is linked to anxiety, depression, and emotional exhaustion, especially among the youth (Ajewumi et al., 2024; Naslund et al., 2020). The results indicate that algorithmic environments are more of psychological stressors than neutral communication tools.

Misinformation, Trust Erosion, and Uncertainty

Algorithmic recommendation systems also have a large role to play in the spread of misinformation. The studies by Chen (2024) and Pathak et al. (2023) show that engagement-focused algorithms tend to boost sensational and emotionally driven material, which can sometimes be at the cost of factual information.

The more misinformation, the more uncertainty, cognitive dissonance and distrust of institutions. Denniss and Lindberg (2025) also show that exposure to misinformation is detrimental to psychological wellbeing and loss of trust in digital ecosystems. These situations add to algorithm anxiety by adding to users' doubts about content reliability and the integrity of the system.

Theoretical Integration

The algorithm anxiety can be theorized using the framework of techno-stress theory (Tarafdar et al., 2015), surveillance capitalism (Zuboff, 2019), uncertainty management theory and media dependency frameworks. The difficulties of adaptation are explained by techno-stress, and the extraction of structural behaviors by surveillance capitalism. Uncertainty management theory helps to understand the emotional reactions to unpredictability of algorithmic systems, and media dependency theory helps to understand the growing dependence on algorithmic infrastructures for information and social validation. These frameworks suggest that algorithm anxiety is a psychological reaction that is produced structurally in algorithmically mediated environments.

Significance

Although there is a lot of research literature regarding digital stress, social media anxiety, and technological dependence, technology anxiety is not well theorized as a multidimensional construct. There is no uniform psychometric tool that is specifically developed to assess emotional responses to algorithmic systems that has been used in previous studies. Furthermore, most studies have concentrated on either the technical design of the algorithms or on psychological outcomes in general, without identifying psychological mechanisms specific to algorithms. In order to overcome this, the present study is developed and validated the Algorithm Anxiety Scale (AAS) by adopting the sequential exploratory mixed-method design. This adds to the psychological measurement literature by providing an algorithm anxiety construct that can be measured, which includes concerns about surveillance, behavioral manipulation, informational uncertainty, and dependency on algorithmic systems.

Aims and Objectives

The primary aim of this study was to develop and validate a psychometrically sound instrument, the Algorithm Anxiety Scale (AAS), for measuring emotional and cognitive responses to algorithm-driven digital environments among social media users.

Method

This study adopted the mixed methods research design that combined the qualitative and quantitative methods in developing and validating the Algorithm Anxiety Scale (AAS). This research was carried out in two stages. The purpose of Phase 1 was to examine the experiences of the participants in relation to algorithm anxiety, using a qualitative phenomenological design. In-depth interviews are used in phenomenology to gain a deep understanding of the subject's experience of the phenomenon. Items for the scale were created in this phase based on the findings. In Phase 2, a quantitative survey design was utilized and the scale created was administered to the respondents through Google Forms.

Phase 1: Qualitative Item Generation

Participants

Phase 1 involved 15 social media users (male and female) who were active users of algorithm-driven platforms like Facebook, Instagram, YouTube and TikTok. Recruitment was done by convenience sampling and the age of the participants ranged from 18-25 years. Participants were university students and professionals who had frequent exposure to algorithmically curated content.

Materials

Demographic Information

Demographic data were gathered including age (18-60 years), gender (male/female) and education (undergraduate level). The participants were a diverse group of university students and professionals who were active on social media platforms on a daily basis.

Interview Guide

The main data collection technique in Phase 1 was semi-structured interviews. The researchers examined previous studies of algorithmic systems, techno-stress, surveillance capitalism, and digital psychology, and created an interview guide to investigate participants' experiences in algorithmic environments. The interview questions focused on emotional responses to algorithmic content such as anxiety, discomfort and stress, on cognitive perceptions of algorithmic control such as unpredictability, lack of transparency and perceived influence, and on behavioral responses to algorithmic exposure such as changes in usage patterns and avoidance behaviors.

Procedure

The ethical approval was obtained from the relevant institutional review board (IRB) before the data collection. Participants were recruited from the university and online communities, and given a brief description of the purpose of the study before they participated. All participants gave informed consent in writing. Confidentiality and anonymity was ensured and participants were told they could drop out of the study at any time without penalty. They were also told the academic intent of the study and any potential for minimal risk of participation. Interviews were held in a private and comfortable environment to minimize response bias and ensure privacy. Before the interviews began, each participant was informed about the structure and purpose of the interviews. The data collection process was standardized to allow methodological consistency across all interviews. Participants were thanked at the end of each interview. There were no monetary or material rewards. Interviews were audio recorded and transcribed in full. Thematic analysis was then done to find the common themes around algorithmic anxiety: emotional distress, feeling out of control, uncertainty about content exposure, and algorithmic influence on behavior. An initial pool of items for the Algorithm Anxiety Scale was created based on the qualitative findings and the theoretical frameworks (techno-stress theory, surveillance capitalism and uncertainty management theory). These items were used as the basis for quantitative validation in Phase 2.

Phase 2: Quantitative Psychometric Validation
Participants

A total of 254 university students and professionals aged 18–60 years were included in the study. Sample consisted of male and female participants with varied educational, occupational and socioeconomic backgrounds. This heterogeneity gave adequate variation in responses to the algorithmic digital experiences and allowed for good psychometric evaluation of the scale.

Materials

Demographic Information

A detailed demographic data was gathered, such as age (18-60 years), gender (Male and Female), education (Undergraduate and Postgraduate), occupation (Student and Professional), family system (Nuclear and Joint) and marital status (Married and Unmarried). The variables were added to capture the characteristics of the sample and explore the potential for differences in anxiety related to the algorithm across demographic groups.

Algorithm Anxiety (AAS)

The Algorithm Anxiety Scale (AAS) was systematically developed in a multi-stage psychometric process that included construct definition, item generation, expert validation, pilot testing, empirical analysis, and scale formation.

Step 1: Test Conceptualization: Algorithm anxiety was conceptualized as a multi-dimensional psychological phenomenon, which includes emotional distress and cognitive uncertainty when interacting with algorithmic digital environments. Emotional reactions (anxiety, worry, discomfort) and cognitive perceptions (lack of control, unpredictability, perceived algorithmic influence) are included in the construct. The definition was based on the techno-stress theory (Tarafdar et al., 2015), surveillance capitalism (Zuboff, 2019) and uncertainty management theory (Brashers, 2001).

Step 2: Item Generation: Items were generated using both inductive and deductive approach. The qualitative interviews with social media users were conducted inductively to gain insight into the experiences of algorithmic systems in everyday life. The deductive item generation was conducted based on the theoretical and empirical studies available on digital psychology, algorithmic governance, and technology-related stress. This process provided for emotional and cognitive aspects of algorithm anxiety coverage.

Step 3: Content Validation: Items in Step 3 were reviewed by experts for clarity, relevance, and representativeness. The conceptual congruence with the defined construct domains was assessed. Content validity was ensured by clarifying and/or eliminating ambiguous, redundant and poorly related items.

Step 4: Pilot testing and item analysis. A pilot study was conducted to examine the item performance, clarity and internal consistency. The item-total correlations and response distributions were studied. The item pool was shortened and enhanced by eliminating and/or modifying items that had low discrimination or poor psychometric characteristics, so it could be administered on a large scale.

Step 5: Empirical Validation (EFA – CFA & Scale Finalization). A larger sample was used to conduct an exploratory factor analysis (EFA) to establish the underlying factor structure of the refined scale. An independent sample was then used for confirmatory factor analysis (CFA) to test the structure. Reliability and validity tests included Cronbach's alpha, composite reliability (CR) and average variance extracted (AVE). Based on these analyses, a final Algorithm Anxiety Scale (AAS) was developed with 12 items, two factors: Emotional Algorithm Anxiety and Algorithmic Control and Uncertainty Perception.

Procedure

Data collection was preceded by ethical approval. Recruitment for participants was done via academic networks and online platforms. All respondents gave informed consent and participation was voluntary. Data was gathered using a structured online questionnaire which was used via Google Forms. The survey consisted of demographic questions and then the Algorithm Anxiety Scale (AAS). Confidentiality, anonymity and the right to withdraw without consequences were explained to the participants. Attention check items were used and data with incomplete responses were not included to assure data quality. The average time to complete was approximately 15-20 minutes. The data were analyzed using IBM SPSS Statistics (Version 28) and IBM AMOS (Version 28). Data screening was done for missing values, normality and outliers. An exploratory factor analysis (EFA) was performed with principal axis factoring and varimax rotation. Confirmatory factor analysis (CFA) was conducted with the final sample of 254 participants, using maximum likelihood estimation.

Results

Psychometric analyses were conducted to examine the factor structure, reliability, and validity of the Digital Over-Parenting Scale. Exploratory factor analysis (EFA) was used to explore the initial factor structure, and confirmatory factor analysis (CFA) was used to test the dimensional structure of the underlying factor structure. The scale was then tested for reliability and construct validity. The results of the analyses are reported in terms of factor structure, model fit indices, and reliability estimates in the following sections.

Table 1
Demographic characteristics of the participants

Variable	Category	f	%
Gender	Male	129	50.8
	Female	125	49.2
Age	18–30	117	46.1
	31–45	107	42.1
	46–60	30	11.8
Education	Matric	28	11.0
	Intermediate	55	21.7
	Bachelor's	113	44.5
	MPhil	56	22.0
	PhD	2	0.8
Socioeconomic Status	Lower	74	29.1
	Middle	170	66.9

Variable	Category	f	%
	Upper	10	3.9
Marital Status	Married	116	45.7
	Unmarried	138	54.3
Occupation	Student	22	8.7
	Unemployed	85	33.5
	Professional	120	47.2
	Part-time worker	27	10.6
Family System	Joint	132	52.0
	Nuclear	122	48.0
Physical Illness	Yes	6	2.4
	No	238	93.7
	Maybe	10	3.9
Psychological Illness	Yes	11	4.3
	No	243	95.7

Note. F = frequency, % = percentage

The sample included 254 participants of both genders. Table 1 shows the demographic profile of the participants. The sample was almost equally distributed according to gender; male 50.8% (n = 129) and female 49.2% (n = 125). The age distribution showed that the majority of respondents were aged between 18 – 30 years (46.1%, n = 117), followed by 31 – 45 years (42.1%, n = 107) and 46 – 60 years (11.8%, n = 30).

When asked about their educational level most of the respondents had a bachelor's degree (44.5%, n = 113), followed by MPhil qualification (22.0%, n = 56), intermediate level education (21.7%, n = 55), matriculation (11.0%, n = 28) and a very small proportion had a PhD degree (0.8%, n = 2). Socioeconomic status revealed that majority of the participants were middle class (66.9%, n = 170), lower socioeconomic status (29.1%, n = 74) and upper socioeconomic status (3.9%, n = 10).

As far as marital status is concerned, 54.3% (n = 138) of respondents were unmarried and 45.7% (n = 116) were married. The distribution of occupations revealed that almost half of the respondents were professionals (47.2%, n = 120), unemployed (33.5%, n = 85), part-time workers (10.6%, n = 27) and students (8.7%, n = 22).

The distribution of family systems showed a relatively even distribution with 52.0% (n = 132) residing in joint family systems and 48.0% (n = 122) in nuclear families. The health-related characteristics revealed that most of the participants indicated that they did not have a physical illness (93.7%, n = 238), whereas 2.4% (n = 6) indicated that they had a physical illness and 3.9% (n = 10) were unsure. Likewise, psychological health status showed 95.7% (n = 243) of the respondents did not have any psychological illnesses, and 4.3% (n = 11) had psychological illnesses.

Table 2
KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.877
Bartlett's Test of Sphericity	Approx. Chi-Square	2950.233
	df	406
	Sig.	<.001

Note. KMO=Kaiser-Meyer-Olkin, df=degree of freedom, Sig=Significance level

To determine the suitability of the data for exploratory factor analysis, Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity were performed. The KMO value was 0.877, which was meritorious, with a value above 0.60, indicating that the data matrix was very suitable for factor analysis. The Bartlett's test of sphericity was statistically significant, $\chi^2(406) = 2950.233$, $p < .001$, which means that the correlation matrix is not an identity matrix and there are enough correlations among the variables to warrant the extraction of factors. All these findings suggest that the data set is suitable for factor analytic procedures and that the use of principal axis factoring for the construction of the Algorithm Anxiety Scale (AAS) is justified.

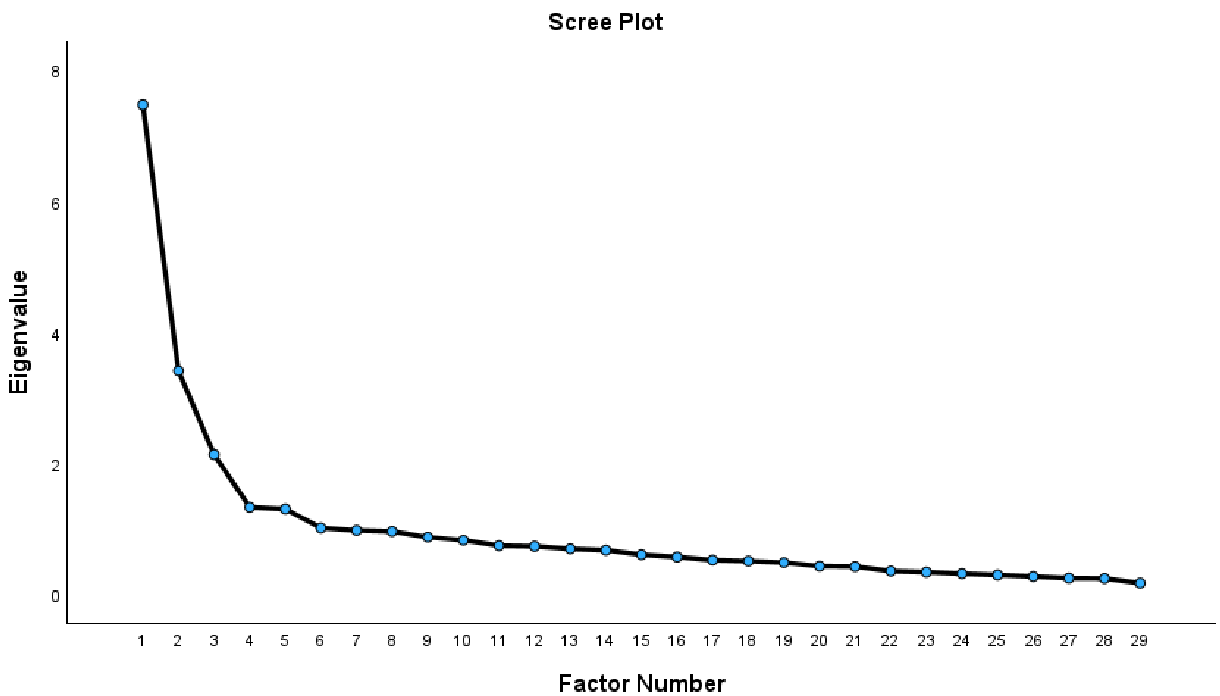

Figure 1
Scree Plot of Eigenvalues for the Digital Over-Parenting Scale

Exploratory factor analysis was used to investigate the underlying structure of the Algorithm Anxiety Scale. The number of factors was decided on using the scree test of Cattell (1966) which involved visual inspection of the eigenvalue plot. The scree plot showed that the eigenvalues dropped rapidly in the first two components and then there was a clear inflection point beyond the second factor.
The first factor had a significantly high eigenvalue, suggesting that the factor is a dominant underlying

dimension of algorithm anxiety. The second factor also had a significant eigenvalue, suggesting the existence of a second latent construct. In addition to the second factor, the curve started to drop off significantly from the third eigenvalue onward, and later eigenvalues dropped almost linearly, showing little extra variation in the data explained. A third factor was noted above the eigenvalue criterion, but this was relatively weaker and did not provide a great deal of separation from the residual variance. Thus, the scree plot offers the best empirical evidence for a two factor solution and indicates that algorithm anxiety is a two-dimensional construct. A three factor structure could be explored as a potential solution, but would need to be further validated with factor loading patterns and confirmatory factor analysis. The overall results suggest that the two factor model is the most parsimonious model for this stage of the analysis.

Table 3

Factor Loadings for the Algorithm-Driven Digital Anxiety and Perception Scale (ADDAPS)

	Factor	
	EAA	ACUP
Using social media makes me feel anxious.	.681	
I feel worried when I spend too much time on social media platforms.	.673	
Exposure to content on social media often makes me emotionally uncomfortable.	.668	
I feel stressed due to the amount of content shown by social media algorithms.	.607	
Advertisements and recommendations on social media make me feel uneasy.	.603	
I feel mentally disturbed when I cannot control what appears on my social media feed.	.584	
I believe social media algorithms influence what I see without my control.		.773
I cannot predict what type of content will appear on my social media feed.		.636
I feel that social media platforms monitor my online behaviour.		.627
I think social media content is selectively shown based on hidden algorithms.		.624
I feel that my online choices are influenced by recommendation systems.		.609
I am unsure why certain posts or advertisements appear on my social media.		.599

Extraction Method: Principal Axis Factoring. Rotation Method: Varimax with Kaiser Normalization. EAA = Emotional Algorithm Anxiety; ACUP = Algorithmic Control & Uncertainty Perception

The Algorithm Anxiety Scale (AAS) was found to have a two factor structure using exploratory factor analysis (principal axis factoring with varimax rotation). The rotated factor loadings for the retained items are shown in Table 4. The first factor was named Emotional Algorithm Anxiety (EAA), and it consisted of items related to emotional responses to algorithmically created content and social media. Moderate to strong positive loadings (ranging from .584 to .681) were found, reflecting a coherent latent dimension of anxiety, worry, emotional discomfort, stress, and unease in algorithm-driven environments. Algorithmic Control and Uncertainty Perception (ACUP) was comprised of items that measured cognitive perceptions of algorithmic systems including lack of control, unpredictability of content, algorithmic influence, and monitoring concerns. The factor loading for this dimension was between .595 and .773, indicating high and consistent item convergence on one latent construct. In general, the factor loading pattern is consistent with a stable two factor solution with well-conceptualized separation between emotional anxiety responses and cognitive perceptions of algorithmic control and uncertainty. Factor loadings for all retained items were ≥ .50, which suggests good contribution to the factors.

Table 4
Reliability of the Algorithm Anxiety Scale and its subscales

Scale/Subscale	Cronbach's Alpha	N of Items
Algorithm Anxiety Scale	.902	12
Emotional Algorithm Anxiety (EAA)	.871	6
Algorithmic Control & Uncertainty Perception (ACUP)	.781	6

The internal consistency of the Algorithm Anxiety Scale (AAS) and subscales were assessed using Cronbach's alpha coefficients. The overall scale had a Cronbach's alpha of .902 for the 12 items, which indicated excellent internal consistency of the items measuring algorithm-related anxiety. The Emotional Algorithm Anxiety (EAA) subscale (six items) also showed high reliability (α = .871), suggesting that the items are reliable in measuring the affective component of algorithm-driven digital environment anxiety. Likewise, the Algorithmic Control and Uncertainty Perception (ACUP) subscale had an acceptable to good internal consistency (α = .781). The reliability results demonstrate that the Algorithm Anxiety Scale (AAS) and its sub-dimensions have satisfactory to good internal consistency, suggesting that the AAS can be used for additional psychometric validation and structural analysis.

Confirmatory Factor Analysis

The validation of the measurement structure of the Algorithm Anxiety Scale (AAS) was conducted in IBM AMOS software with confirmatory factor analysis. The proposed model included two latent constructs correlated with each other: Emotional Algorithm Anxiety (EAA) and Algorithmic Control and Uncertainty Perception (ACUP). Maximum likelihood estimation was used to test the two-factor structure to see how well it fit the observed covariance matrix.

Construct validity was evaluated using the CFA results, which included an overall model fit and the relationships between the observed indicators and the latent variables without the removal of any items. The loading of all items on their corresponding latent constructs were significant, thus supporting the stability of the proposed measurement model. The Emotional Algorithm Anxiety (EAA) factor was the affective responses to anxiety, worry, emotional discomfort, and stress in algorithmic digital environments, while the Algorithmic Control and Uncertainty Perception (ACUP) factor was the cognitive perceptions of algorithmic influence, unpredictability, and lack of user control. The CFA confirmed the proposed two-factor structure of the Algorithm Anxiety Scale (AAS), indicating a good model fit of the algorithm related psychological experiences in digital environments.

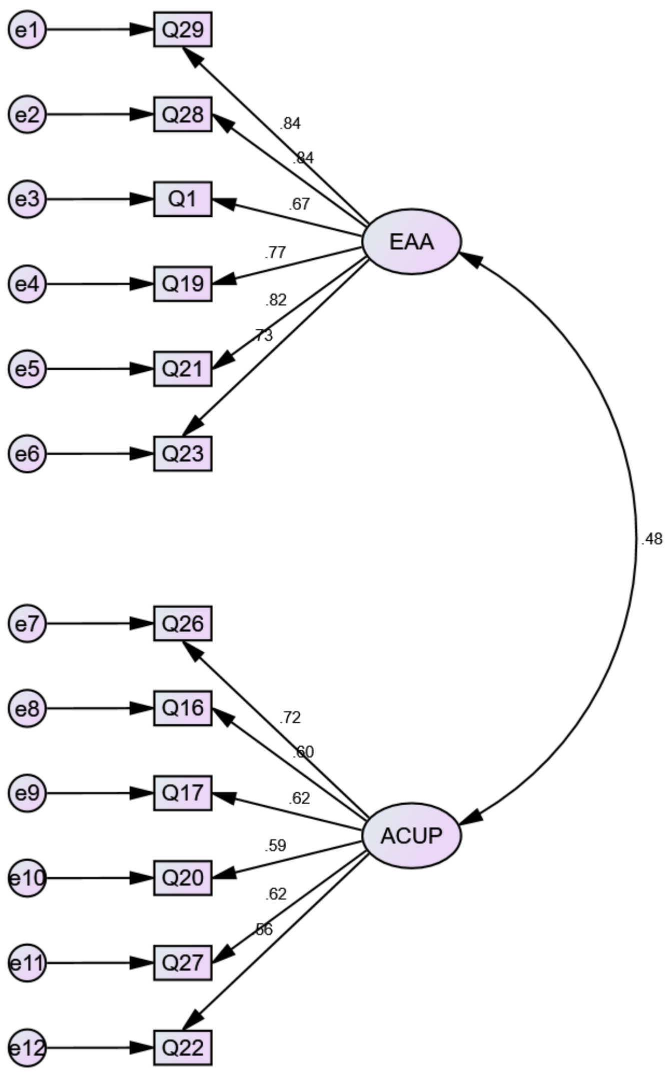

Figure 2
CFA Path Diagram for Algorithm Anxiety Scale

Confirmatory factor analysis (CFA) with maximum likelihood estimation method was used to test the measurement model of Algorithm Anxiety Scale (AAS) using IBM AMOS. The proposed model contained two factors: Emotional Algorithm Anxiety (EAA) and Algorithmic Control and Uncertainty Perception (ACUP).
The standardized CFA results showed that all the indicators observed loaded significantly and strongly on the respective latent constructs. The standardized loadings for the Emotional Algorithm Anxiety (EAA) factor ranged from .67 to .84, which showed good association between the observed variables (Q1, Q19, Q21, Q23, Q28, Q29) and the latent construct of emotional. The results support the validity of EAA to assess affective reactions such as anxiety, worry and emotional discomfort to algorithm-driven digital environments.
Likewise, the standardized loadings of the Algorithmic Control and Uncertainty Perception (ACUP) factor were high (between .59 and .72) for

the items of the factor (Q16, Q17, Q20, Q22, Q26, Q27) indicating that they consistently measure the perceived lack of control, unpredictability, and algorithmic influence in digital platforms.

The correlation between the two latent constructs was moderate (r = .48), meaning that there is a relationship between the two constructs, but they are empirically distinct. This supports discriminant validity between the two constructs. The CFA results support the factorial validity of the Algorithm Anxiety Scale (AAS) and the two-factor measurement model proposed, which is statistically valid and theoretically coherent in capturing algorithm-related psychological experiences.

Table 6

Model Fit Indices for the Measurement Model of the Algorithm Anxiety Scale

Fit Index	Estimate	Threshold	Interpretation
χ^2 (CMIN)	103.301	–	–
Df	53	–	–
χ^2/df	1.949	1.00–3.00	Excellent
CFI	0.961	> 0.95	Excellent
SRMR	0.066	< 0.08	Good
RMSEA	0.061	≤ 0.06–0.08	Acceptable
PClose	0.141	> 0.05	Excellent

Note. χ^2 = chi-square statistic; df = degrees of freedom; CFI = comparative fit index; SRMR = standardized root mean square residual; RMSEA = root mean square error of approximation; PClose = p-value for test of close fit.

The measurement model of the Algorithm Anxiety Scale (AAS) was assessed by confirmatory factor analysis (CFA) with maximum likelihood estimation (MLE) using IBM AMOS. The hypothesized model comprised two factors: Emotional Algorithm Anxiety (EAA) and Algorithmic Control and Uncertainty Perception (ACUP), which were both affective (emotional) and cognitive (perception) psychological responses to algorithms.

The overall model fit indices showed the proposed measurement model to be a good fit to the observed data. The normed chi-square (χ^2/df) was 1.949 with 53 degrees of freedom (df), which is within the recommended range of 1.0 to 3.0, suggesting excellent model parsimony.

The model was also supported by incremental fit indices. The Comparative Fit Index (CFI) was .961, which is higher than the .95 recommended value, thus suggesting an excellent comparative fit. The Standardized Root Mean Square Residual (SRMR) was .066, which is less than the acceptable .08, indicating good residual fit.

The Root Mean Square Error of Approximation (RMSEA) was .061, which falls within the range of .05 to .08, considered acceptable approximation error. In addition, the PClose value was .141, which is greater than .05, indicating good model fit. Overall, the CFA results showed that the two factor structure of the Algorithm Anxiety Scale (AAS) is acceptable and theoretically coherent, which means that the measurement model is factually valid.

Table 7

Construct Validity of the Algorithm Anxiety Scale (AAS)

Construct	CR	AVE	MaxR(H)	r (EAA–ACUP)
Emotional Algorithm Anxiety (EAA)	0.903	0.608	0.911	0.483
Algorithmic Control & Uncertainty Perception (ACUP)	0.787	0.382	0.793	0.483

Note. CR = Composite Reliability; AVE = Average Variance Extracted; MaxR(H) = Maximum Reliability (H); r = inter-construct correlation.

The Algorithm Anxiety Scale (AAS) was evaluated for its construct validity by composite reliability (CR), average variance extracted (AVE), and maximum reliability (MaxR(H)). The results are shown in Table 7.

The composite reliability for the Emotional Algorithm Anxiety construct was high (CR = 0.903), surpassing the recommended threshold of 0.70, suggesting good internal consistency among the indicators. The average variance extracted (AVE = 0.608) was higher than the recommended value of 0.50, indicating good convergent validity. Strong construct reliability was also confirmed by the maximum reliability (MaxR(H) = 0.911).

The composite reliability for the Algorithmic Control and Uncertainty Perception (ACUP) construct was acceptable (CR = 0.787) and was greater than the minimum acceptable value of 0.70. The AVE value (AVE = 0.382) was below the suggested value of 0.50 which indicated a low convergent validity for this construct, meaning that the items measure the construct only moderately and with some measurement error. The maximum reliability of the construct was 0.793 for the MaxR(H) value.

The inter-construct correlation was compared with the square root of AVE to evaluate the discriminant validity. The correlation between EAA and ACUP was 0.483, which is lower than the square root of AVE for EAA (√AVE = 0.780), indicating acceptable discriminant validity between the two latent constructs. However, because the AVE for ACUP is not high enough than the recommended value, its convergent validity is relatively low and needs to be improved in future research. The measurement model is generally valid for the Emotional Algorithm Anxiety construct, and has acceptable reliability and convergent validity for the Algorithmic Control and Uncertainty Perception construct, although it is comparatively less valid. Overall, the structure of the items is consistent with the theoretical separation of emotional anxiety responses and cognitive perceptions of algorithmic control in the Algorithm Anxiety Scale (AAS).

Discussion

The present study conceptualized the Algorithm Anxiety Scale (AAS) as a multidimensional scale measuring psychological reactions to algorithm-based digital environments and developed it. The present study was aimed at developing and validating Algorithm Anxiety Scale (AAS) as a multidimensional scale measuring psychological reactions to algorithm-based digital environments. This finding aligns with evidence that algorithmic systems shape structured psychological experience that are opaque, predictable, and adaptive with regard to the delivery of content (Beer, 2017; Gillespie 2018; Kitchin, 2017).

The rise of a dual structure is in line with socio-technical approaches that consider algorithms as active mediators of perception instead of mere computational instruments (Seaver, 2017). Algorithmic anxiety can then be seen as a kind of "plat-formed subjectivity" that is a constant emotional and cognitive negotiation in algorithmically curated contexts (Couldry & Mejias, 2019).

Emotional Algorithm Anxiety (EAA) as Affective Algorithmic Stress

Emotional Algorithm Anxiety (EAA) factor is emotional reaction to anxiety, worry, stress, discomfort and unease in algorithmic environments. The results align with emerging studies that show that algorithmic personalization increases emotional involvement by curating content according to the likelihood of user reaction, instead of emotional health (Zuboff, 2019; Bucher, 2018).

Algorithmic environments operate cyclically, feeding into engagement with content and raising emotional reactivity (Pariser, 2011; Tufekci, 2015). This aligns with the computational persuasion research that suggests that algorithmic systems are designed to drive engagement, and to amplify emotions rather than information (O'Neil, 2016; Noble, 2018).

In the psychological dimension, the EAA dimension follows the ideas of the techno-stress theory (Tarafdar et al., 2015) that stress in digital environments is not only a function of the complexity of the systems, but also a function of the algorithms that shape behavior. Unlike the traditional ICT stressors, algorithmic systems are adaptive, and create emotionally charged environments that are constantly changing in response to user interaction patterns (Beer, 2017; Zuboff, 2019).

Moreover, the emotional volatility that can be seen in algorithmic environments could be associated with attentional fragmentation and cognitive overload due to constant content re-ranking and personalization (Carr, 2011; Nguyen et al., 2020). This indicates that emotional algorithm anxiety is not just a by-product of the psychological experience, but is structurally built into the platform design.

Algorithmic Control and Uncertainty Perception (ACUP)

The Algorithmic Control and Uncertainty Perception (ACUP) factor reflects cognitive perceptions of algorithmic systems such as the feeling of not being in control, uncertainty, algorithmic influence, and concerns about monitoring. The results are consistent with theories of algorithmic opacity, which suggest that users are increasingly faced with systems that they are unable to meaningfully interpret or interrogate (Gillespie, 2018; Pasquale, 2015).

Theoretically, ACUP is also rooted in surveillance capitalism (Zuboff, 2019), which sees digital platforms as systems designed to harvest behavioral data for the purpose of creating predictive models of future behavior. In these systems, users are less empowered because of the information and control asymmetries between platforms and users (Srnicek, 2017).

The idea that content is algorithmically manipulated behind the scenes is a reflection of what Pariser (2011) calls “filter bubbles”, or “epistemically limited informational environments” that users are exposed to. This adds to the confusion over the personal preference or algorithmic manipulation of digital experiences (Bucher, 2018).

The convergent validity in ACUP (AVE = 0.382) is also in line with previous studies that indicate that cognitive interpretations of algorithmic systems can be diverse and shaped by digital literacy, platform familiarity, and socio-technical awareness (Noble, 2018; Cotter, 2021). Cognitive perceptions are more likely to be influenced by interpretive frameworks, resulting in variation in measurement consistency, compared to emotional responses.

Relationship between emotional and cognitive dimensions

Moderate correlation between EAA and ACUP (r = .48) indicates a relationship between emotional anxiety and cognitive perceptions of algorithmic control, but they are not identical constructs. This helps to explain dual process theories of psychological reactions in which the cognitive evaluation of uncertainty is linked to emotional reactions (Lazarus & Folkman, 1984; Lerner & Keltner, 2001).

A sense of lack of control and informational uncertainty can serve as antecedents of emotional distress in algorithmic environments. Emotional anxiety can also be triggered independently, however, due to repeated exposure to algorithmically optimized content streams, there are partially autonomous emotional mechanisms that are built into platform design (Tufekci, 2015; Zuboff, 2019).

Emotional anxiety can also be triggered independently, however, due to repeated exposure to algorithmically optimized content streams, there are partially autonomous emotional mechanisms that are built into platform design

(Tufekci, 2015; Zuboff, 2019). This is significant, because it moves beyond algorithmic anxiety as a single psychological state to an algorithmic process that involves cognitive interpretation and emotional activation in a digital system.

Theoretical Contributions

The study is grounded in the literature of the algorithmic society and the concept of algorithm anxiety is introduced as a multidimensional phenomenon. This study is unique from other studies looking at digital stress or social media fatigue in general, because it specifically examines psychological mechanisms related to algorithms. The present study makes three important contributions to the literature. First, it builds on the concept of techno-stress theory (Tarafdar et al., 2015) by adding two additional stressors: algorithmic unpredictability and behavioral influence. The findings here, instead of the traditional techno-stress models that focus on overload and complexity, point to algorithmic opacity and behavioral modulation as other dimensions of stress.

Second, it helps to empirically operationalize psychological reactions to algorithmic governance structures, thereby advancing the theory of surveillance capitalism (Zuboff, 2019). This is in contrast to much of the previous research, which has been conceptual, and this study offers empirical evidence of emotional and cognitive impacts of algorithmic systems.

Thirdly, it contributes to the fields of communication and media theory by empirically separating emotional affect from cognitive appraisal in algorithmic contexts. This is in line with recent calls for psychological models to be combined with platform studies to better understand the interaction between users and algorithms (Bucher, 2018; Couldry & Mejias, 2019).he present study contributes to the literature in three key ways.

Practical Implications

The Algorithm Anxiety Scale (AAS) is a validated tool to measure psychological vulnerability in algorithmic environments. The implications for digital well-being interventions are especially relevant in contexts where users are inundated with algorithmic personalization, like social media, streaming services, and search engines. The results also align with the policy recommendations for algorithmic transparency and explainability, which are known to cause cognitive uncertainty and emotional distress (Pasquale, 2015; Floridi et al., 2018). Increasing the awareness of algorithmic processes by users could help to decrease the sense of uncertainty and increase digital resilience. The scale can be used in educational and clinical settings to identify those who are experiencing high levels of algorithm-related anxiety, and provide specific interventions to enhance digital coping and lower technology-induced stress.

Limitations and Recommendations

While the study has made contributions, it also has some limitations. The convergent validity of the ACUP construct was low and needs to be improved. Further research is needed to determine if ACUP is a distinct construct or part of other constructs, such as digital literacy or algorithm awareness (Noble, 2018). In addition, the cross-sectional design does not allow for causal inferences. Future research should investigate the development of algorithm anxiety over time and if repeated exposure to algorithmic environments leads to increased emotional and cognitive reactions.

There is also a need for further research to validate across platforms, as there are significant differences in algorithmic architecture across platforms (e.g., TikTok, YouTube, Instagram, and Facebook), which may have different psychological impacts (Cotter, 2021; Bucher, 2018). Also, there is a need for cross-cultural validation since the perception of algorithmic control may vary across socio-cultural contexts, regulatory frameworks and digital literacy (Srnicek, 2017).

Conclusion

The Algorithm Anxiety Scale (AAS) was developed and validated in the present study, which showed the existence of a reliable two-factor structure: Emotional Algorithm Anxiety (EAA) and Algorithmic Control and Uncertainty Perception (ACUP). The results demonstrate that algorithmic environments evoke emotional distress and cognitive uncertainty, which can be described as a new psychological phenomenon: algorithm anxiety. The scale demonstrated good reliability and validity, thus it can be used in empirical studies of digital behavior and algorithmic systems. In conclusion, the AAS is a validated tool to advance the research on psychological reactions to algorithmic environments in existing digital societies.

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