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The Sociology of Emotions on Digital Platforms: Attention Economy, Emotion Management, and Emotional Exhaustion among Indian Users

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ABSTRACT

Digital platforms derive economic value from user attention, and emotionally charged expression is among the most effective means of attracting it. Drawing on Hochschild's sociology of emotion management, attention-economy theory, and Bourdieu's field theory, this study examines how users' engagement with attention-economy logics is associated with emotion management, emotional ambivalence, and emotional exhaustion in India, a setting in which everyday platform use spans domestic platforms and global ones under an active regime of app blocking and internet shutdowns. A cross-sectional online survey was completed by 384 active users aged 18–45, recruited through convenience and snowball sampling. Data were analyzed using Pearson correlations, one-way ANOVA, independent-samples *t*-tests, and structural equation modeling. Mean scores for the attention economy ($M = 3.80$) and emotion management ($M = 3.90$) were above the midpoint of the five-point scale. The attention economy was strongly correlated with emotion management ($r = .68$), and emotional ambivalence was correlated with emotional exhaustion ($r = .59$). In the structural model, the attention economy predicted emotion management ($\beta = .71$), emotion management predicted emotional ambivalence ($\beta = .65$), and emotional ambivalence predicted emotional exhaustion ($\beta = .57$); a smaller direct path from the attention economy to emotional ambivalence was also observed ($\beta = .22$), and the serial indirect association of the attention economy with emotional exhaustion through emotion management and emotional ambivalence was significant ($\beta = .26$). Instagram users reported higher emotion management than Telegram users, and women reported more digital emotional labor than men. The findings are consistent with the argument that platforms convert emotional expression into an attention-generating resource, thereby extending emotion management from the workplace into everyday digital life, with psychological costs that are unevenly distributed across platforms and genders. Because the design is cross-sectional and non-probabilistic, the associations should not be interpreted as causal effects.

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1. INTRODUCTION

1.1. Background and Problem Statement

Digital platforms have become some of the most consequential arenas of social, cultural, and economic interaction in contemporary societies. They do not simply transmit messages between people; through their interfaces, metrics, and ranking systems, they also shape how emotions are experienced, displayed, and regulated [1]. A comment, a story, or a short video is at once an act of communication and a performance staged before an audience whose reactions are counted, ranked, and returned to the user in the form of visible metrics. The emotional life of users is therefore increasingly lived within infrastructures designed by commercial actors for commercial ends.

The concept of the attention economy captures the logic of these infrastructures. Its starting point is the observation that, in an information-rich environment, human attention becomes the scarce resource [2]. Subsequent work argued that attention would become the central economic resource of networked societies [3] and a key currency of business [4], and more recent scholarship describes attention as a universal symbolic currency on social media and beyond [5]. Because platforms earn revenue primarily by selling access to user attention, they have strong incentives to privilege content that captures and holds it. Empirical research shows that emotionally arousing content is shared more widely than neutral content [6] and that moral-emotional language increases the diffusion of messages in online networks [7]. Emotion thus becomes one of the most efficient instruments for producing engagement.

Within this environment, emotion management is no longer only a private or interpersonal matter. It becomes a structurally patterned requirement for those who wish to be seen, heard, or paid. Qualitative research with professional gamers, influencers, and gig and crowd workers shows that the affordances of digital work platforms demand extensive emotional labor from their users [8], and similar demands have been documented among ordinary users and followers, not only among professional content producers [9]. Users must decide which feelings to display, how intensely, and to whom, and they receive continuous quantitative feedback on how successful these decisions have been.

These developments raise a sociological problem that has received comparatively little empirical attention. If emotional expression is rewarded with visibility, users may face persistent pressure to curate their feelings in line with what platforms and audiences reward. In organizational research, a sustained gap between felt and displayed emotion has been consistently associated with emotional exhaustion [10]. Whether comparable dynamics operate in everyday platform use, and how they are distributed across platforms and social groups, remains insufficiently understood.

The Indian case is particularly revealing in this respect. Indian users move between domestic platforms, such as ShareChat and Moj, and international platforms, while the state has blocked several widely used foreign apps (most notably TikTok since 2020) and frequently orders content removals and regional internet shutdowns [11]. Social media in India has also long served as a space of political, cultural, religious, and gendered expression [12]. Indian users are therefore exposed simultaneously to the commercial logic of global platforms and to the normative expectations of the domestic sociopolitical and cultural environment. This combination makes India a useful setting for examining how emotional display is shaped by attention-economy logics and by social norms at the same time.

1.2. Research Gap, Aims, and Contributions

Existing research leaves at least four gaps. First, much of the literature on social media and emotion is psychological in orientation: it examines individual well-being, emotion regulation, or emotional intelligence, frequently among adolescents [1, 13–15]. Less attention has been paid to how platform economics structures emotional conduct as a social practice. Second, research on emotional labor in digital settings has been predominantly qualitative and has focused on professional creators and platform workers [8, 16]; quantitative evidence on ordinary users remains limited. Third, few studies have modeled the attention economy, emotion management, emotional ambivalence, and emotional exhaustion jointly as a sequence of related processes. Fourth, non-Western contexts, including India, are underrepresented in this literature, even though their platform ecologies differ substantially from those of the countries in which most theories were developed.

The present study addresses these gaps by combining the sociology of emotions, platform studies, and the political economy of digital media. Its aims are threefold: (a) to describe the extent to which Indian users engage with attention-economy logics and practice emotion management on digital platforms; (b) to examine the relationships among the attention economy, emotion management, emotional ambivalence, and emotional exhaustion within an integrated structural model; and (c) to assess whether emotion management differs across primary platforms and between women and men.

The study makes three contributions. Theoretically, it extends Hochschild's account of emotion management from occupational settings to everyday platform use and proposes emotional ambivalence as a mechanism linking platform-induced emotion management to emotional exhaustion. Empirically, it provides quantitative evidence from an understudied context characterized by a hybrid ecology of domestic and international platforms under active state regulation of online content. Practically, it identifies groups and platform environments in which the emotional costs of participation appear to be concentrated, which has implications for platform design, media literacy, and mental health promotion.

2. THEORETICAL FRAMEWORK AND LITERATURE REVIEW

2.1. From Emotion Work to Digital Emotional Labor

The sociological study of emotions owes much of its contemporary vocabulary to Arlie Russell Hochschild. Hochschild argued that emotions are governed by socially shared feeling rules, which specify what people ought to feel in particular situations, and that individuals perform emotion work to bring their feelings into line with these rules [17]. In *The Managed Heart*, she distinguished this private emotion management from emotional labor, in which the management of feeling is sold for a wage and the worker's emotional display becomes part of the commodity being sold [18]. She also distinguished surface acting, in which displayed emotion is altered without changing inner feeling, from deep acting, in which individuals attempt to change the feeling itself [18]. Her analysis showed how capitalism appropriates not only the physical and cognitive capacities of workers but also their inner emotional lives, and her later work traced how market logics penetrate intimate life more broadly [19].

This framework provides a foundation for understanding how emotions are transformed into economic resources on digital platforms. On these platforms, users, often without regarding it as work, engage in a new and extensive form of digital emotional labor through the production and display of emotional content. Studies of digital work platforms show that their affordances require workers to manage emotions continuously in order to secure visibility, ratings, and income [8]. Research on fashion bloggers demonstrates that self-branding depends on the display of a carefully curated, positive, and seemingly authentic self [16], while research on Instagram followers indicates that audiences, too, perform emotional labor in sustaining the relationships on which platform visibility depends [9]. Social media use has also been examined as a factor in the relationship between emotional labor and burnout among public-sector employees [20], which suggests that the boundary between occupational and everyday emotional labor is increasingly porous.

In this study, digital emotional labor is defined as the regulation of felt and displayed emotion in order to present a desirable image to networked audiences in exchange for attention, recognition, or income. The term "labor" is used deliberately even when no wage is paid: the emotional effort of users generates data and engagement from which platforms derive economic value.

2.2. The Attention Economy and the Commodification of Emotion

The idea that attention is scarce in an information-rich world was articulated by Simon, who argued that an abundance of information consumes, and therefore makes scarce, the attention of its recipients [2]. Goldhaber developed this insight systematically for the internet age and predicted that attention would become the principal economic resource of the networked environment [3]. Davenport and Beck subsequently analyzed attention as the new currency of business [4], and Heitmayer has recently argued that social media have accelerated a broader shift in which attention functions as a universal symbolic currency [5].

In this environment, platforms compete intensely to attract and retain a limited resource, because selling users' attention to advertisers constitutes their primary business model. Emotion becomes the most powerful instrument in this competition. Content that evokes high-arousal emotions, whether positive (such as awe) or negative (such as anger or anxiety), is more likely to be shared than content that evokes low-arousal emotions such as sadness [6], and each additional moral-emotional word in a political message has been associated with greater diffusion on social networks [7]. Engagement, measured through views, likes, comments, and shares, thus functions as the currency of the emerging economy, and emotional intensity is one of the most reliable ways of generating it.

This dynamic has consequences for users' emotional lives. Scholars have argued that platform strategies for maximizing engagement can undermine digital well-being and users' capacity for self-regulation [15], and that the emotional affordances of social media shape which emotions are elicited, expressed, and reinforced [1]. Research on young people has linked problematic social media use to difficulties in emotion regulation and lower emotional intelligence [14], although recent discussions also emphasize that social media can support emotion regulation and that blanket restrictions may overlook such benefits [13]. Taken together, this literature suggests that the attention economy is not emotionally neutral: it rewards particular emotional displays and thereby creates incentives for users to manage their emotions strategically.

2.3. Algorithms, Data Extraction, and Emotional Amplification

The role of platforms in shaping emotion is not limited to rewarding certain displays. Andrejevic's analysis of automated media shows how digital systems collect behavioral data at scale and use automated processing to anticipate and influence behavior [21]. Applied to emotion, this logic can be described as emotional data extraction: likes, comments, shares, viewing duration, and the sentiment of textual content are recorded and used not only for targeted advertising but also to train systems that classify, predict, and potentially modulate users' emotional states. Within this model, human emotions become a raw material for value production, and users become the sources from which this material is extracted.

Ranking algorithms add a further layer. Feeds that prioritize content according to predicted engagement do not merely respond to users' emotions; they participate in producing them. Because emotionally charged and polarizing content tends to generate more engagement [6, 7], engagement-based ranking can create an emotional feedback loop in which certain emotions, particularly those that are fast, intense, and predictable, are amplified and reproduced. Platform architecture can also standardize expressive forms. Zulli and Zulli show that TikTok's affordances encourage imitation and replication, giving rise to what they call imitation publics organized around shared templates [22]. When such templates carry emotional scripts, users learn not only what to post but also how to feel, or appear to feel, about it. The result can be described as an economization of emotion, in which feelings are implicitly ranked and valued according to their capacity to generate attention.

2.4. Emotional Capital, Platform Fields, and Inequality

Pierre Bourdieu's concepts of capital and field provide a framework for analyzing how platforms reproduce and reshape social inequality [23]. Platforms can be understood as social fields whose rules of interaction are set largely by platform owners and encoded in algorithms. Within these fields, displayed emotions can function as a form of emotional capital that is convertible into social capital (networks of relationships) and symbolic capital (recognition, reputation, and prestige). The concept of emotional capital has been developed within the Bourdieusian tradition to describe emotional resources that are unevenly distributed and strongly gendered [24].

Individuals who are better able to produce and display emotions in accordance with platform algorithms and audience norms gain competitive advantages in visibility and influence. This process may reproduce existing inequalities and create new hierarchies based on what may be called digital emotional competence. Gender is likely to be a central axis of this stratification. Hochschild observed that emotional labor is disproportionately performed by women [18], and research on digital self-branding shows that women creators are expected to display upbeat, intimate, and authentic-seeming emotional selves [16]. These considerations suggest that the emotional demands of platforms are not borne equally.

2.5. Emotional Politics and the Indian Platform Context

Emotion management on platforms also has a political dimension. Nye's concept of soft power describes the capacity of states and institutions to shape preferences through attraction rather than coercion [25]. Digital platforms have become important arenas in which governments and other powerful actors attempt to steer public emotions toward particular political and social objectives, for example through targeted content production, the cultivation of artificial trends, the moderation or removal of content expressing undesirable emotions, and the promotion of particular emotional narratives. In more restrictive environments, these practices may acquire a coercive character and become instruments for engineering emotional cohesion around preferred political orientations.

In India, these dynamics intersect with the attention economy in distinctive ways. Global platforms such as Instagram, YouTube, and X dominate everyday use, while domestic platforms grew rapidly after the 2020 ban on TikTok and other foreign apps, and the state retains extensive powers to block content and suspend internet access [11]. Research on digital cultures in South Asia documents how online platforms have served as spaces of political mobilization, gender negotiation, cultural production, and state presence [12]. Indian users therefore operate in an intermediary space: they are exposed to the global attention economy and the algorithms of international platforms, and also to governmental emotional politics and to specific cultural, caste, and religious norms.

This study proposes that such conditions are likely to produce emotional ambivalence, defined here as a discrepancy between the emotions individuals display and those they actually experience. Users may display one set of normatively approved emotions on domestic platforms that are perceived as more public or more closely monitored, and a different, sometimes contradictory set of emotions in the more semi-private spaces of international platforms. The problem of managing multiple audiences is not unique to India: when diverse audiences collapse into a single online context, users must balance authenticity against self-censorship [26]. In the Indian setting, however, the stakes of this balancing act are heightened by political and cultural sensitivities. At the same time, platforms may become spaces of emotional resistance in which emotions suppressed in physical public settings can be expressed.

2.6. Integrative Framework and Hypotheses

Taken together, these perspectives suggest that digital platforms are complex social institutions that redefine human emotion along several dimensions at once: as emotional labor [18], as extractable data [21], as an instrument for attracting attention [4], as a stimulus for algorithmic ranking [22], as a form of capital within a field [23], and as an object of political management [25]. Through these processes, emotion is transformed from an internal and personal state into an external economic resource. This study conceptualizes the outcome of this transformation as a tendency toward an algorithmically emotion-managed society, in which the boundaries between authentic and performed emotion, and between human agency and technological steering, become increasingly blurred.

At the level of individual users, this framework implies a sequence of processes. Users who are more strongly oriented toward attention-economy logics, that is, who are more motivated by likes and feedback, more willing to produce engaging content, and more sensitive to metrics, are expected to engage in more intensive emotion management. Because emotion management on platforms frequently takes the form of surface acting, it is expected to widen the gap between felt and displayed emotion, producing emotional ambivalence. Organizational research indicates that such emotional dissonance is among the most robust predictors of emotional exhaustion [10]. Attention-economy orientation may also contribute to ambivalence directly, for example through social comparison and exposure to idealized emotional displays. The following hypotheses were therefore formulated (Figure 1):

- H1.** The attention economy is positively associated with emotion management.
- H2.** Emotion management is positively associated with emotional ambivalence.
- H3.** Emotional ambivalence is positively associated with emotional exhaustion.
- H4.** The attention economy is positively and directly associated with emotional ambivalence.
- H5.** Emotion management and emotional ambivalence sequentially mediate the association between the attention economy and emotional exhaustion.
- H6.** Women report higher levels of digital emotional labor than men.

In addition, the study addresses one research question: **RQ1**. Does emotion management differ according to users' primary platform?

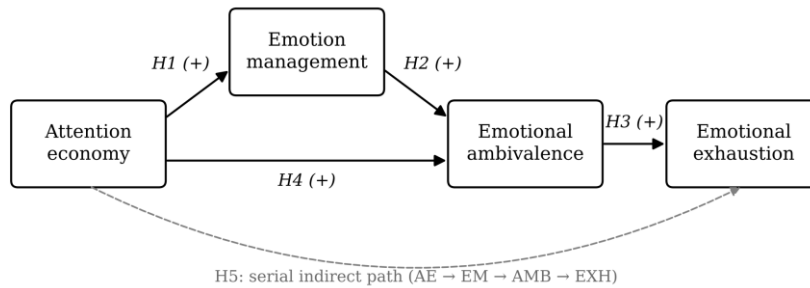


Fig. 1. Conceptual model of the study. Solid arrows denote hypothesized direct paths (H1–H4); the serial indirect path from the attention economy to emotional exhaustion through emotion management and emotional ambivalence corresponds to H5 (dashed arrow). AE = attention economy; EM = emotion management; EMB = emotional ambivalence; EXH = emotional exhaustion.

3. METHOD

3.1. Research Design

In terms of its objective, this study is applied research; in terms of data collection, it is a descriptive survey with a cross-sectional correlational design. The methodological approach is quantitative, and an online questionnaire served as the primary instrument for data collection.

3.2. Population, Sampling, and Participants

The statistical population consisted of active Indian users of digital platforms aged 18 to 45 years, including users of domestic platforms (ShareChat and Moj) and international platforms (Instagram, Telegram, and Twitter, now X). Eligibility was based on self-report: respondents were Indian users aged 18–45 who reported using at least one of these platforms and indicated their primary platform and average daily time of use. Given the size and geographic dispersion of the population and the absence of a sampling frame, non-probability convenience and snowball sampling were used. The questionnaire was distributed online through social networks, messaging groups, and online survey forms.

The target sample size of 384 corresponds to Cochran's formula for a large population at a 95% confidence level and a $\pm 5\%$ margin of error [27]. Because sampling was non-probabilistic, however, this figure is not interpreted as guaranteeing representativeness. The adequacy of the sample for structural modeling was therefore also assessed with the inverse square root method [28]: for the smallest path coefficient in the model ($\beta = .22$), a significance level of .05, and statistical power of .80, the method indicates a minimum of approximately 128 cases, which the final sample comfortably exceeds. The final analytic sample comprised 384 participants.

3.3. Instrument

The questionnaire consisted of four sections. Items were rated on a five-point scale ranging from 1 (lowest) to 5 (highest), and construct scores were computed as item means, so that higher scores indicate higher levels of the construct.

Demographic information. This section recorded participants' age, gender, educational level, average daily use of digital platforms, and primary platform of use.

Attention economy. This researcher-developed scale assessed key dimensions of users' engagement with attention-economy logics, including motivation to obtain likes and feedback, willingness to produce engaging and

widely shared content, perceived competition for attention, and sensitivity to engagement metrics. Because the attention economy is a structural property of platforms, the construct was measured at the individual level as users' orientation toward, and perceived exposure to, these logics.

Emotion management. This researcher-developed scale was informed by the theoretical work of Hochschild [18] and Andrejevic [21]. It assessed digital emotional labor (regulating emotions to present a desirable image), emotional self-censorship, and conformity to platform emotional norms. Digital emotional labor was also analyzed as a separate subscale in the gender comparison.

Emotional ambivalence. This scale assessed the perceived discrepancy between the emotions users display on platforms and the emotions they actually experience. Ambivalence items were scored as a separate construct and were not included in the emotion management score.

Experienced consequences. This section assessed users' perceived consequences of participation, including emotional exhaustion, feelings of alienation, reduced intimacy in offline relationships, and changes in self-perception. The present article focuses on emotional exhaustion, the outcome most directly implicated by the theoretical model and by previous research on emotional labor; the remaining outcomes are beyond the scope of this analysis and are noted as a direction for future research.

3.4. Validity and Reliability

Content validity was assessed by a panel of experts in sociology, social psychology, and media studies, and the items were revised on the basis of their feedback. Reliability was first examined in a pilot sample of 30 members of the target population, with Cronbach's $\alpha \geq .70$ adopted as the criterion for each scale. Item-level output for the main sample was not available when this article was prepared. Internal consistency, composite reliability (CR), average variance extracted (AVE), and heterotrait–monotrait (HTMT) ratios for the final sample [29, 30] are therefore not reported, and this is acknowledged as a limitation (Section 5.8).

Because all variables were measured with self-reports from a single source at a single time point, common method variance was a potential concern [31]. To reduce this risk procedurally, the questionnaire was anonymous and the predictor and outcome measures were presented in separate sections. Because common method variance could not be ruled out statistically, it is acknowledged as a limitation (Section 5.8).

3.5. Data Analysis

Data were analyzed in two stages. In the first stage, descriptive statistics (means, standard deviations, frequencies, and percentages) were computed in SPSS to describe the sample and the main constructs. In the second stage, inferential analyses were conducted: Pearson correlation coefficients were used to examine bivariate associations among the constructs; a one-way analysis of variance (ANOVA) with Tukey's post hoc test was used to compare emotion management across primary platforms (RQ1); and an independent-samples *t*-test was used to compare digital emotional labor between women and men (H6). Finally, structural equation modeling (SEM) was used to test H1–H4, and the significance of each path was evaluated with its *t*-statistic. The serial indirect effect specified in H5 was estimated as the product of the standardized path coefficients, and its standard error was derived with the multivariate delta method for three-path mediated effects [32, 33]. The significance level was set at .05 for all tests.

4. RESULTS

4.1. Sample Characteristics

The final sample comprised 384 participants. Of these, 58% were women and 42% were men. With respect to age, 39% of participants were aged 18–25 years, 35% were aged 26–35 years, and 26% were aged 36–45 years. Instagram was the most frequently reported primary platform (45%), followed by Telegram (30%), domestic platforms such as ShareChat and Moj (13%), and Twitter (12%). The mean daily time spent on digital platforms was 3.5 hours ($SD = 1.2$). Table 1 summarizes these characteristics.

Table 1. Demographic Characteristics of the Sample (N = 384)

Variable	Category	%
Gender	Women	58
	Men	42
Age group	18–25 years	39
	26–35 years	35
	36–45 years	26
Primary platform	Instagram	45
	Telegram	30
	Twitter (X)	12
	Domestic platforms (ShareChat, Moj)	13
Daily platform use (hours)	$M = 3.5, SD = 1.2$	—

Note. Percentages are based on N = 384 (women: $n = 223$; men: $n = 161$).

4.2. Descriptive Statistics of the Main Constructs

Table 2 presents the means and standard deviations of the four main constructs. All construct means exceeded the scale midpoint of 3. Emotional ambivalence had the highest mean ($M = 4.00, SD = 0.88$), followed by emotion management ($M = 3.90, SD = 0.81$) and the attention economy ($M = 3.80, SD = 0.76$). Emotional exhaustion had the lowest mean ($M = 3.60, SD = 0.91$) but remained above the midpoint. These results indicate that, on average, participants reported substantial engagement with attention-economy logics and substantial emotion management on digital platforms.

Table 2. Descriptive Statistics of the Main Research Constructs (Scale: 1–5)

Construct	<i>M</i>	<i>SD</i>	Interpretation
Attention economy	3.80	0.76	Above midpoint
Emotion management	3.90	0.81	Above midpoint
Emotional ambivalence	4.00	0.88	Above midpoint
Emotional exhaustion	3.60	0.91	Above midpoint

Note. Interpretation is relative to the theoretical midpoint of the scale (3).

4.3. Correlations Among the Main Constructs

As shown in Table 3, all correlations among the four constructs were positive and statistically significant ($p < .01$), ranging from .48 to .68. The strongest association was observed between the attention economy and emotion management ($r = .68$), followed by the association between emotion management and emotional ambivalence ($r = .65$). Emotional ambivalence was more strongly correlated with emotional exhaustion ($r = .59$) than were emotion management ($r = .52$) and the attention economy ($r = .48$), a pattern consistent with the proposed sequence.

Table 3. Pearson Correlation Matrix Among the Main Research Constructs (N = 384)

Construct	1	2	3	4
1. Attention economy	—			
2. Emotion management	.68**	—		
3. Emotional ambivalence	.55**	.65**	—	
4. Emotional exhaustion	.48**	.52**	.59**	—

Note. ** $p < .01$ (two-tailed).

4.4. Structural Model

Table 4 presents the direct paths in the structural model. The attention economy was positively associated with emotion management ($\beta = .71$, $t = 8.92$, $p < .01$), supporting H1. Emotion management was positively associated with emotional ambivalence ($\beta = .65$, $t = 7.84$, $p < .01$), supporting H2, and emotional ambivalence was positively associated with emotional exhaustion ($\beta = .57$, $t = 6.95$, $p < .01$), supporting H3. The direct path from the attention economy to emotional ambivalence was also significant but considerably smaller ($\beta = .22$, $t = 3.12$, $p < .01$), supporting H4. The reported fit indices were CFI = .93 and RMSEA = .06, which fall within commonly used thresholds of acceptable fit.

Table 4. Direct Paths in the Structural Model

No.	Path	β	t	p
H1	Attention economy → Emotion management	.71	8.92	< .01
H2	Emotion management → Emotional ambivalence	.65	7.84	< .01
H3	Emotional ambivalence → Emotional exhaustion	.57	6.95	< .01
H4	Attention economy → Emotional ambivalence	.22	3.12	< .01

Note. β = standardized path coefficient. Fit indices: CFI = .93, RMSEA = .06.

To test H5, the serial indirect effect of the attention economy on emotional exhaustion through emotion management and emotional ambivalence was estimated as the product of the three standardized path coefficients ($.71 \times .65 \times .57$), with standard errors derived from the reported t -values using the multivariate delta method [32, 33]. The serial indirect effect was significant ($\beta = .26$, $SE = .06$, $z = 4.49$, $p < .001$, 95% CI [.15, .38]). The specific indirect effect through emotional ambivalence alone (attention economy → emotional ambivalence → emotional exhaustion) was also significant ($\beta = .13$, $SE = .04$, $z = 2.85$, $p = .004$, 95% CI [.04, .21]). H5 was therefore supported. Because the delta method assumes a normal sampling distribution for the product of coefficients, these estimates are conservative relative to bootstrap-based tests and are reported with this caveat.

4.5. Differences in Emotion Management Across Platforms

A one-way ANOVA indicated that emotion management differed significantly across primary platforms, $F(3, 380) = 9.32$, $p < .001$ (Table 5). Based on the reported sums of squares, the effect size was $\eta^2 = .07$, indicating a medium effect. Tukey's post hoc test showed that Instagram users ($M = 4.10$) reported significantly higher emotion management than Telegram users ($M = 3.60$, $p < .01$). The remaining pairwise differences were not statistically significant.

Table 5. One-Way ANOVA of Emotion Management by Primary Platform

Source of variation	Sum of squares	df	Mean square	F	p
Between groups	18.45	3	6.15	9.32	< .001
Within groups	250.80	380	0.66		
Total	269.25	383			

Note. F = between-groups mean square / within-groups mean square ($6.15 / 0.66$). $\eta^2 = .07$, computed from the sums of squares.

4.6. Gender Differences in Digital Emotional Labor

As shown in Table 6, women ($M = 4.00$, $SD = 0.75$) reported significantly higher levels of digital emotional labor than men ($M = 3.70$, $SD = 0.80$), $t(382) = 3.89$, $p < .001$. Based on the reported descriptive statistics, this corresponds to a small-to-medium effect size (Cohen's $d = 0.39$). H6 was therefore supported.

Table 6. Independent-Samples t-Test of Digital Emotional Labor by Gender

Group	n	M	SD	t	df	p	Cohen's d
Women	223	4.00	0.75	3.89	382	< .001	0.39
Men	161	3.70	0.80				

Note. Digital emotional labor is a subscale of emotion management. Cohen's d was computed from the reported means and standard deviations.

4.7. Summary of Hypothesis Testing

Table 7 summarizes the results of hypothesis testing.

Table 7. Summary of Hypothesis Testing

No.	Statement	Result
H1	Attention economy → Emotion management (+)	Supported
H2	Emotion management → Emotional ambivalence (+)	Supported
H3	Emotional ambivalence → Emotional exhaustion (+)	Supported
H4	Attention economy → Emotional ambivalence (+)	Supported
H5	Serial mediation via emotion management and emotional ambivalence	Supported
H6	Women > men in digital emotional labor	Supported
RQ1	Differences in emotion management by primary platform	Instagram > Telegram; other differences not significant

5. DISCUSSION

This study examined how users' engagement with attention-economy logics is related to emotion management, emotional ambivalence, and emotional exhaustion on digital platforms in India. The results support a coherent pattern: users who are more strongly oriented toward attention and engagement report more intensive emotion management; more intensive emotion management is associated with a larger gap between displayed and felt emotion; and this gap is in turn associated with greater emotional exhaustion. The following sections interpret these findings, relate them to theory and previous research, and identify their contributions.

5.1. The Attention Economy and Emotion Management

The strong association between the attention economy and emotion management (H1) is consistent with the central claim of attention-economy theory, namely that when attention becomes the scarce and valued resource, actors adapt their conduct to capture it [3–5]. Because emotionally arousing and moral-emotional content attracts more engagement [6, 7], users who care about likes, shares, and visibility have a clear incentive to calibrate their emotional displays accordingly. The finding also accords with qualitative evidence that platform affordances demand extensive emotional labor from creators and platform workers [8]. The present study extends this evidence in two respects: it shows that the association holds among a broad sample of ordinary users rather than only professional creators, and it quantifies its strength in a non-Western setting.

From the perspective of Hochschild's theory, this finding suggests that feeling rules on platforms are increasingly written by metrics [17, 18]. Whereas the flight attendants studied by Hochschild learned feeling rules through corporate training and supervision, platform users learn them through quantified audience feedback. The commercialization of feeling that Hochschild identified in service work thus appears to have extended into everyday sociability, where it operates without an explicit employer but in the service of platforms' economic interests. The high mean level of emotion management in the sample suggests that this is not a marginal practice but a routine feature of platform participation.

5.2. From Emotion Management to Emotional Ambivalence and Exhaustion

The paths from emotion management to emotional ambivalence (H2) and from emotional ambivalence to emotional exhaustion (H3) provide a plausible mechanism through which the attention economy may affect users' well-being. These results closely parallel the organizational literature, in which surface acting, the display of emotions that are not felt, is one of the most consistent predictors of emotional exhaustion [10]. Emotional ambivalence as measured here is conceptually close to the emotional dissonance produced by surface acting. The present findings suggest that the costs of dissonance are not confined to paid service work; they also arise when individuals continuously present curated emotional selves to networked audiences.

Two features of platforms may make this dissonance especially taxing. First, unlike a service encounter, platform self-presentation has no clear end: content remains visible and continues to accumulate reactions, so the performance is effectively permanent. Second, platform audiences are heterogeneous. When friends, family, colleagues, and strangers are collapsed into a single audience, users must manage competing expectations simultaneously [26], which makes it more difficult to align displayed emotion with any single authentic response. The relatively high mean level of emotional ambivalence in the sample ($M = 4.00$) is consistent with this interpretation.

The smaller direct path from the attention economy to emotional ambivalence (H4) indicates that attention-economy orientation may produce ambivalence not only through deliberate emotion management but also through other routes. One plausible route is social comparison: users who monitor metrics closely are continuously exposed to idealized emotional displays by others, which may heighten their awareness of the gap between their own feelings and what appears to be expected. This interpretation is consistent with arguments that platform engagement strategies can undermine digital well-being and self-regulation [1, 15], but it should be tested directly in future research.

At the same time, two qualifications are necessary. First, the attention economy and emotion management were also directly correlated with emotional exhaustion ($r = .48$ and $.52$). The significant serial indirect effect supports H5, but because direct paths from these constructs to exhaustion were not part of the reported model, it cannot be concluded that emotional ambivalence fully mediates their associations with exhaustion. Second, because the data are cross-sectional, the sequence proposed here is one theoretically grounded ordering among several possible ones. It is also plausible, for instance, that emotionally exhausted users experience greater ambivalence about their online presence. Longitudinal data would be needed to establish temporal precedence.

5.3. Platform Differences in Emotion Management

In response to RQ1, emotion management was higher among users whose primary platform was Instagram than among those whose primary platform was Telegram, whereas the other platform comparisons were not significant.

This pattern can be interpreted in terms of platform affordances. Instagram is organized around visual self-presentation, public profiles, and highly visible metrics, all of which place users' emotional selves on continuous display and invite evaluation. Telegram, by contrast, is used largely for messaging and channel-based content consumption, in which personal emotional display is less central and audience metrics are less salient. Research on the emotional affordances of social media suggests that such design features shape which emotions are elicited and displayed [1], and research on fashion bloggers demonstrates that visually oriented platforms place a premium on curated, positive self-presentation [16].

Two aspects of this finding warrant caution. First, the effect was of medium size ($\eta^2 = .07$), indicating that platform type accounts for only a modest share of the variance in emotion management. Second, the ANOVA compared levels of emotion management; it did not test whether the relationships in the structural model differ across platforms. The claim that the entire pathway from the attention economy to exhaustion is stronger on visually oriented platforms would require a multi-group analysis. It is also notable that users of domestic platforms did not differ significantly from users of other platforms. This finding does not support the expectation that the normative pressures associated with domestic platforms would produce distinctive levels of emotion management, although the relatively small size of this subgroup (13% of the sample) limits statistical power for this comparison.

5.4. Gender and the Unequal Distribution of Emotional Labor

Women reported significantly more digital emotional labor than men (H6). This result is consistent with Hochschild's observation that emotional labor is disproportionately performed by women [18] and with the Bourdieusian argument that emotional capital is gendered [24]. It also aligns with research showing that women's self-presentation on social media is subject to strong expectations of positivity, intimacy, and authenticity [16]. Within the platform field, therefore, the emotional requirements of visibility appear to fall more heavily on women. If emotional labor contributes to exhaustion, as the structural model suggests, this unequal distribution may translate into unequal psychological costs. In the Indian context, gendered norms governing public emotional expression may further intensify these demands, although this possibility could not be tested directly with the present data.

5.5. The Indian Context

The Indian context helps to explain why emotional ambivalence emerged as a central construct in this study. Indian users move between domestic platforms and international platforms within a regulatory environment marked by app bans, content-takedown orders, and internet shutdowns [11], and these environments differ in their audiences, in their perceived degree of monitoring, and in the norms governing acceptable emotional expression. Previous research has shown that social media in South Asia has served both as a space of dissent and self-expression and as a space in which state and partisan actors are present [12]. Under these conditions, the management of emotion is shaped not only by the commercial logic of attention but also by political and cultural considerations. Users may experience pressure to display particular emotions for visibility and, simultaneously, to suppress others for reasons of safety or social acceptability.

This dual pressure may help to explain the high mean level of emotional ambivalence observed in the sample. At the same time, the finding that domestic-platform users did not differ significantly from others in emotion management suggests that the emotional demands of platform participation may be relatively general across platform types, at least at the level captured by the present measures. Comparative studies across countries with different platform regimes would help to determine which features of the findings are specific to India and which reflect the global attention economy.

5.6. Theoretical Contributions

The study contributes to theory in three ways. First, it extends the sociology of emotions by showing that Hochschild's concepts of emotion management and emotional labor [17, 18] can be meaningfully applied to everyday platform use, where metrics replace managerial supervision as the source of feeling rules. Second, it integrates the sociology of emotions with attention-economy theory [3, 4] and with critical analyses of automated media [21] by specifying a mechanism, from attention-economy orientation through emotion management and emotional

ambivalence to emotional exhaustion, that links the political economy of platforms to users' emotional experience. Third, by situating these processes within a Bourdieusian account of platform fields and emotional capital [23, 24], it highlights that the costs of the attention economy are socially distributed, notably along gender lines and across platform environments.

5.7. Practical Implications

The findings have several practical implications. For platform designers and regulators, they suggest that the prominence of public engagement metrics may intensify emotion management and its associated costs; design options such as allowing users to hide metrics, or reducing the weight of engagement signals in ranking, merit evaluation. For educators and mental health professionals, the results support the development of digital emotional literacy, that is, the capacity to recognize how platform incentives shape emotional display and to set boundaries on emotional performance. Interventions may be particularly relevant for women and for heavy users of visually oriented platforms. For organizations that rely on staff or creators to maintain a social media presence, the results indicate that such work entails emotional labor that should be acknowledged in workload planning and support.

5.8. Limitations and Directions for Future Research

Several limitations should be considered when interpreting the findings. First, the cross-sectional design precludes causal inference; the structural paths represent associations consistent with the proposed model rather than demonstrated effects. Longitudinal or experience-sampling designs would allow the temporal ordering of attention-economy orientation, emotion management, ambivalence, and exhaustion to be examined. Second, non-probability convenience and snowball sampling limit the generalizability of the findings to the population of Indian platform users; samples recruited online tend to over-represent more active and more educated users. Third, all constructs were measured by self-report from a single source, which raises the possibility of common method variance [31] and may have inflated the observed correlations. Fourth, the scales were developed by the researcher, and only content validity and pilot reliability are documented; reliability and validity statistics for the main sample (α , CR, AVE, and HTMT) are not reported. Measurement quality in the final sample therefore cannot be fully evaluated, and further psychometric validation, including confirmatory factor analysis in independent samples, is needed. Fifth, the attention economy was measured at the individual level, as users' orientation toward attention-economy logics, rather than as a structural property of platforms; future studies could combine survey data with platform-level data on metrics and ranking. Sixth, participants were classified by a single primary platform, although most users are active on several platforms. Finally, indirect effects were tested with the delta method on the basis of the estimated path coefficients; bootstrap confidence intervals and the estimation of direct paths to emotional exhaustion would provide a more complete test of the mediation model.

Future research could address these limitations and extend the present findings in several directions: testing whether the structural relationships differ across platforms and genders through multi-group analysis; examining additional outcomes such as alienation, offline intimacy, and self-perception; incorporating moderators such as self-esteem, emotional intelligence, and political engagement; using qualitative methods to explore how users experience and negotiate emotional ambivalence across platforms; and conducting cross-national comparisons to separate the effects of the global attention economy from those of specific national contexts.

6. CONCLUSION

This study set out to provide a sociological examination of emotions on digital platforms, focusing on the interrelated concepts of the attention economy and emotion management in the Indian context. The findings, derived from a survey of 384 active users, suggest that digital platforms are not neutral communication technologies but socio-technical environments that shape, regulate, and mediate emotional expression and interaction. By transforming attention into a scarce and valuable resource and emotional engagement into a driver of platform activity, these systems influence both individual experience and broader social relations.

At the individual level, users appear to engage in continuous emotional regulation and self-presentation in response to the demands of visibility, interaction metrics, and audience expectations. Consistent with Hochschild's

concept of emotional labor, digital environments extend emotion management beyond occupational settings into everyday life. This process is associated with emotional ambivalence, a discrepancy between authentic and displayed feelings, which is in turn associated with emotional exhaustion. Sustained emotional performance may therefore carry psychological costs that accumulate over time.

The study also highlights the role of platform algorithms. Engagement-based ranking tends to amplify emotionally charged, easily shareable, and highly visible forms of expression, giving users incentives to display emotions in ways that maximize visibility. This dynamic may contribute to the standardization of emotional expression and to forms of emotional communication optimized for engagement rather than authenticity.

At the meso- and macro-social levels, digital platforms can be understood as emerging social fields in which emotional expression functions as a form of social and symbolic capital. Individuals who are more adept at displaying emotions in digitally visible ways may obtain advantages in attention, influence, and recognition. The gender differences observed in this study indicate that emotional labor is not equally distributed and may reflect broader social expectations regarding emotional expression. Digital environments may thus both reproduce existing inequalities and generate new forms of stratification based on visibility and emotional performance.

In the Indian context, users navigate multiple digital environments with different norms, audiences, and communicative practices, which creates a complex and multilayered emotional landscape. Taken together, the findings suggest that contemporary platforms are increasingly woven into the emotional fabric of everyday life, raising questions about emotional well-being, authenticity, privacy, and digital citizenship. Addressing these questions requires not only technological and regulatory responses but also the development of digital emotional literacy, enabling users to understand critically and to manage the emotional demands of digitally mediated environments. A deeper understanding of these processes can contribute to digital environments that support both meaningful social interaction and psychological well-being.

Conflict of interest

The author declares no conflict of interest.

Ethical Considerations

Participation was voluntary. Before beginning the questionnaire, participants were informed of the purpose of the study, the anonymity of their responses, and their right to withdraw at any time, and they provided informed consent. No personally identifying information was collected.

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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