

Attention on social media depends more on how you express yourself than on who you are

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Attention has become a vital form of capital in the digital age, yet the mechanisms underlying its allocation on social media remain poorly understood. Using a nationally representative, online and offline-integrated dataset of a Generation Z cohort in China, we provide large-scale evidence on the determinants of success in attracting attention. Our findings reveal that ‘how you express yourself’ (using various emojis and expressing multiple emotions) is more influential than ‘who you are’ (in terms of gender, education, family background and personality traits) in attracting attention on social media. Further analysis confirms a causal effect of the variety of emojis and types of emotions on attracted attention, while simulation processes using agent-based models suggest that empathy evocation is the primary underlying mechanism. We also show that the mode of expression is largely independent of individual characteristics and that the attention gained from highly appealing expressions is easier to acquire than to sustain, as it is highly sensitive to changes in expression modes over time. Overall, our research identifies three key features of attention capital allocation on social media: low alignment with traditional resources, considerable manipulability and ease of acquisition but difficulty sustaining it over time.

In an era of overabundant information, attention has become an increasingly scarce resource^{1,2}. Economists regard attention as a valuable commodity in short supply and refer to the cyberspace-based economy as the ‘attention economy’^{3–5}, in which businesses and media compete to secure and maintain consumers’ limited attention for success^{6–8}. The rise of Web 2.0 technologies and the growing popularity of social media platforms has transformed ordinary people from passive information consumers into active content producers^{9,10} who must also compete for limited attention in a finite population. For individuals, attention obtained on social media platforms may bring about a larger social impact^{11–13}, generate more opportunities in job markets^{14,15}, drive additional income^{16,17}, lead to higher perceived social support^{18,19} and cultivate higher levels of self-esteem²⁰. Attention can thus be positioned as a new form of capital²¹ that not only reaps profits for businesses but

may generate an advantageous position and other desirable resources for individuals in the digital era.

The importance of attention capital leads to a crucial set of questions: Who is more likely to acquire it? Moreover, is the allocation of attention capital affected by offline resources such that advantaged groups extend their superiority to the online space? Existing research on traditional and non-traditional celebrities suggests mixed answers in these regards^{22–24}. Traditional celebrities with established popularity as sports stars, movie icons or political or business elites are more approachable on social media than on other platforms; they can easily attract a large group of followers, transforming their offline advantages into attention capital. On the other hand, a substantial number of ordinary content providers (for example, bloggers, vloggers, Instagrammers and live streamers) have achieved grassroots

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success as social media stars. Through efforts such as self-branding^{25–27}, managing authenticity^{28–30}, enhancing follower interactions^{31–33} and navigating algorithmic rules^{34,35}, these figures gain enough fame that their attracted attention and advertising effectiveness may rival that of traditional celebrities^{36,37}.

Moreover, traditional or non-traditional celebrities collectively account for only a minor proportion of social media users. For example, among Instagram's ~2 billion monthly active users³⁸, there are ~5.63 million (0.28%) with over 10,000 followers, and among these, only ~343,000 (0.002%) are celebrities with over 1 million followers³⁹. However, the existing literature has focused almost exclusively on celebrities, offering few insights into how attention capital is allocated among the rest of the population—over 99% of users on social media platforms—and the mechanisms underlying its allocation. This narrow focus is akin to concentrating solely on elite groups in economics or sociology while neglecting the general public. In an era where attention capital has been gaining prominence, it is clear that examining only a select few is insufficient. There is a pressing need to explore how the majority of users acquire and accumulate attention, as they are the main force sustaining the attention economy and also important competitors for attention capital. Therefore, our research aims to include ordinary users in the scope of investigation for a comprehensive understanding of the allocation logic behind this new form of capital.

One of the main obstacles to this goal, however, is the anonymous nature of ordinary users. Beyond the small minority of users whose offline identities are recognizable, the sociodemographic backgrounds of most users on most social media platforms are not publicly available. This leads to two challenges. First, even if researchers can observe attracted attention among ordinary users, they can hardly ascertain who these users are, and they are therefore unable to examine the relationship between their attracted attention and their existing resources. Second, social media users of any platform are self-selected and seldom represent the general population or even a targeted sub-population. Owing to the anonymity of users, this self-selection bias is difficult to correct, leading to additional challenges in reaching a general conclusion in our study context.

Therefore, to achieve our research goal, we first drew a nationally representative sample of a Generation Z cohort—specifically, the 2013 middle school entry cohort, with most individuals born in 2000–2001—and conducted offline surveys to collect sociodemographic background data. We then collected three full years (2018–2021) of data on their public posts and interactions from WeChat, China's largest social media platform. The majority of respondents were aged 17–18 years at the beginning of online data collection and 20–21 years by its conclusion. The dataset includes only posts and associated interactions that were accessible to the research team; posts with private settings were not available. Over the 3-year period, approximately 2.1 million online posts and interactions were collected. For those who provided informed consent, we further linked their online records to their offline survey information.

We selected WeChat for this study for three main reasons. First, as the largest and most popular social media platform in China, WeChat has over 1.4 billion monthly active users. With a usage rate covering approximately 75% of China's population⁴⁰—which is nearly equivalent to the entire internet user base in China⁴¹—WeChat has minimal selection bias for studying attention among the general public. Second, interactions on WeChat are grounded in users' real-life social networks, eliminating the influence of fake followers and artificial engagement that have been reported on many other social media platforms^{42,43}. Third, public posts on WeChat are displayed chronologically on users' browsing pages rather than being algorithmically sorted or recommended, which can influence information spreading and the dynamics of attention^{44,45}. Thus, WeChat presents an ideal setting for studying users' natural browsing behaviours and attention allocation mechanisms with minimal platform interference.

Based on the integrated dataset combining online and offline information, we investigated how attention capital is allocated among the public and what drives this allocation. Specifically, we focused on two sets of determinants: the first includes sociodemographic attributes and personal traits ('who you are'), and the second is the mode of expression ('how you express yourself'). The former captures one's structural position and human capital in the offline world, while the latter reflects one's expressive characteristics in the online space. Although the former is known to influence access to many traditional forms of resources, its role in obtaining attention—an emerging form of capital in the digital age—remains unclear. In this paper, we compared its effect with that of the mode of expression in gaining attention, analysed the correlation between the two sets of factors and examined the mechanisms that shape the distribution of attention capital. We also used an open-access Twitter dataset to assess the generalizability of our key findings and implemented randomized controlled trials to evaluate causal relationships. On the basis of our findings, we identified three distinctive features in the allocation of attention capital and discussed their implications in the digital era.

Results

'How you express yourself' versus 'who you are'

On the WeChat platform, users can post updates to their Moments, where their verified friends or acquaintances may click 'like' or leave comments on these posts. Considering the different implications of liking and commenting on social media⁴⁶, we constructed different networks for the two types of online behaviours separately and calculated the node centrality of a user based on how much attention they attracted. By employing network analysis instead of merely counting the raw number of likes or comments a user received, we could analyse the user's attractiveness and comprehensively assess the importance of a node in the constructed attention networks.

Using the constructed liking and commenting networks, we measured attracted attention employing (1) incoming edges, or the number of contacts from whom a given user has received likes/comments; (2) weighted incoming edges, which employs the number of likes/comments from each contact as a weight. By taking into account the interaction frequency between users and their contacts, this measure indicates the total number of likes/comments a user has received; (3) net incoming edges, or the number of 'pure fans' from whom a user has received net likes/comments after reciprocal interactions are removed; and (4) weighted net incoming edges, which uses the number of net likes/comments from each 'pure fan' as a weight, and which is also the total number of likes/comments a user has received from 'pure fans'. The first two measurements focus on the overall attention attracted to a node, whereas the latter two exclude attention obtained in reciprocal interactions—which might be out of courtesy—and focus on unilateral attractiveness.

For each of the four measurements of attracted attention, we evaluated the importance of a node in the attention networks using four different metrics: degree centrality, betweenness centrality, PageRank centrality and DomiRank centrality. In total, 16 centrality metrics were constructed for attracted attention in the liking network and another 16 in the commenting network. While degree and betweenness centralities focus on the number of direct connections and the bridging role of a node, respectively, the other two measure a node's importance by considering the characteristics of its neighbours, each using a different approach (for more details, see Methods). As each metric provides a distinct perspective on node importance, we included all in our analysis to ensure robustness and to provide a comprehensive view of the results. When space constraints limit what can be shown, centrality metrics based on incoming edges are reported in the main text, with the full set of results included in the Supplementary Information.

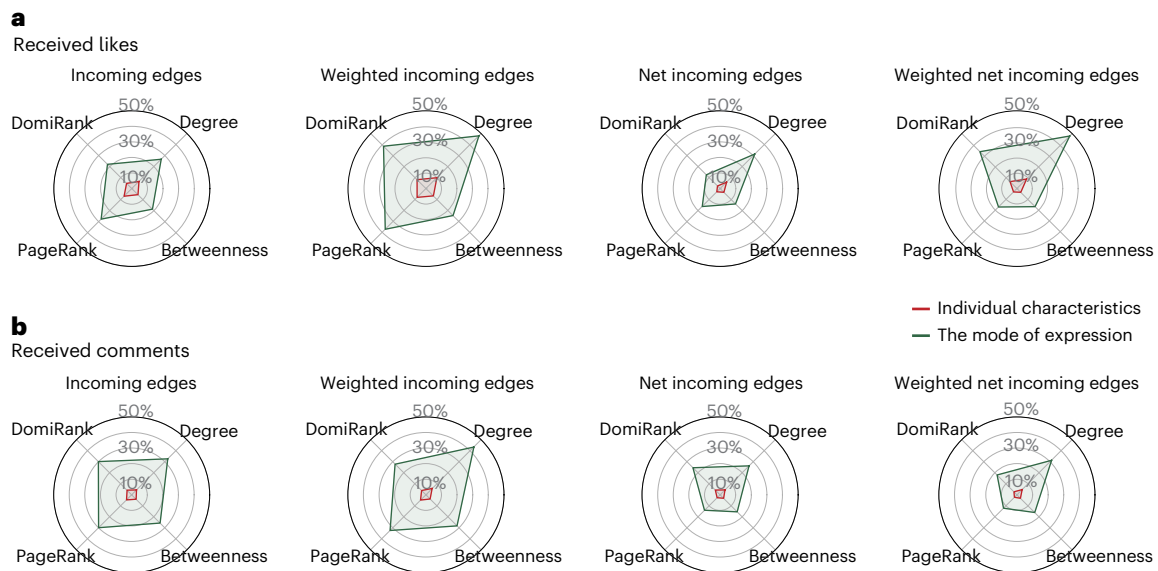


Fig. 1 | Explanatory power (marginal R^2) of two sets of variables based on multilevel models. a,b. Marginal R^2 of ‘who you are’ (red lines) versus ‘how you express yourself’ (green lines) on attracted attention in the liking network (a) and in the commenting network (b). Attracted attention is measured by incoming

edges, weighted incoming edges, net incoming edges and weighted net incoming edges. Four centrality metrics are employed for each measurement to indicate the importance of a node in the attention network. $N = 2,206$.

We focused on two sets of determinants underlying attention attraction on social media platforms: the mode of expression (‘how you express yourself’) and individual characteristics (‘who you are’). We measured ‘how you express yourself’ with three indicators: the average text length of posts, the variety of emojis and types of emotions. The rationale underlying the selection of these three indicators is detailed in Supplementary Note 1, while the specific methods used to measure them are described in Supplementary Note 2. ‘Who you are’ was indicated by several sociodemographic attributes and personal traits, including gender, highest educational level, family background and the Big Five personality traits (extraversion, openness, agreeableness, conscientiousness and neuroticism). The Methods present a more detailed description of these variables.

Owing to the hierarchical structure of the dataset (students nested within schools), we used multilevel models to examine the effects of the two sets of variables on node centralities, based on different measures of attracted attention. Then, we calculated marginal R^2 to indicate their explanatory powers (the conditional R^2 values that take random effects into account are shown in Supplementary Fig. 6)⁴⁷. As shown in Fig. 1, the explanatory powers of ‘who you are’ are less than 10% across all node centrality metrics of all measurements of attracted attention in both liking and commenting networks. By contrast, the explanatory powers of ‘how you express yourself’ are much larger, accounting for up to 49% of the variation in attracted attention.

We also conducted two additional analyses in which we examined the explanatory powers of ‘how you express yourself’ after allowing for the number of posts and after controlling for ‘who you are’. Neither analysis showed appreciable augmentations in explanatory powers, suggesting that once the mode of expression is accounted for, the level of engagement in social media and individual characteristics have trivial effects on enhancing attracted attention. This finding is consistent across all measurements in the networks, based on likes and comments (for details, see Supplementary Fig. 7).

Next, we used the attracted attention as measured by incoming edges to visualize the results of individual variable coefficients. All continuous variables were standardized in the model estimation (Fig. 2; for results based on alternative measurements,

see Supplementary Figs. 8–10). Among the indicators of ‘how you express yourself’ (Figs. 2a,c), the findings show that the average text length of posts is not associated with attracting attention, whereas the variety of emojis and types of emotions exhibit consistently significant positive associations with received likes and comments. We conducted robustness analyses that took into account potential social and contextual confounders, such as individuals’ offline popularity and social media usage patterns. The associations between modes of expression and attracted attention remained consistent (for details, see Supplementary Figs. 11–14).

Regarding indicators of ‘who you are’ (Figs. 2b,d), gender and the personality traits of neuroticism and extraversion show positive associations with attractiveness across all metrics, although they may not be significant in some other measures of attracted attention, as shown in Supplementary Figs. 8–10. Apart from these, no other individual characteristics showed significant correlations with attracted attention in either liking or commenting networks.

Overall, the results indicate that, compared with individual characteristics, modes of expression have a substantially stronger association with attracted attention on WeChat, especially the variety of emojis and types of emotions. To determine whether these associations are specific to WeChat, we conducted a supplementary analysis using a Twitter dataset, which yielded highly consistent results. Specifically, modes of expression again demonstrated strong explanatory power for attracted attention, with R^2 ranging from 43% to 53%. Notably, both the variety of emojis and types of emotions consistently showed significant positive associations with attracted attention (for more details, see Supplementary Note 5), providing cross-platform support for our findings.

The causal effect of the mode of expression on attracted attention

To determine whether the mode of expression has a causal effect on attracted attention, we conducted additional analyses using fixed-effects models and instrumental variables models. Since the variety of emojis and types of emotions were identified as key factors, we focused on these two dimensions of expression. The Methods provide details on the analytical approaches and model specifications.

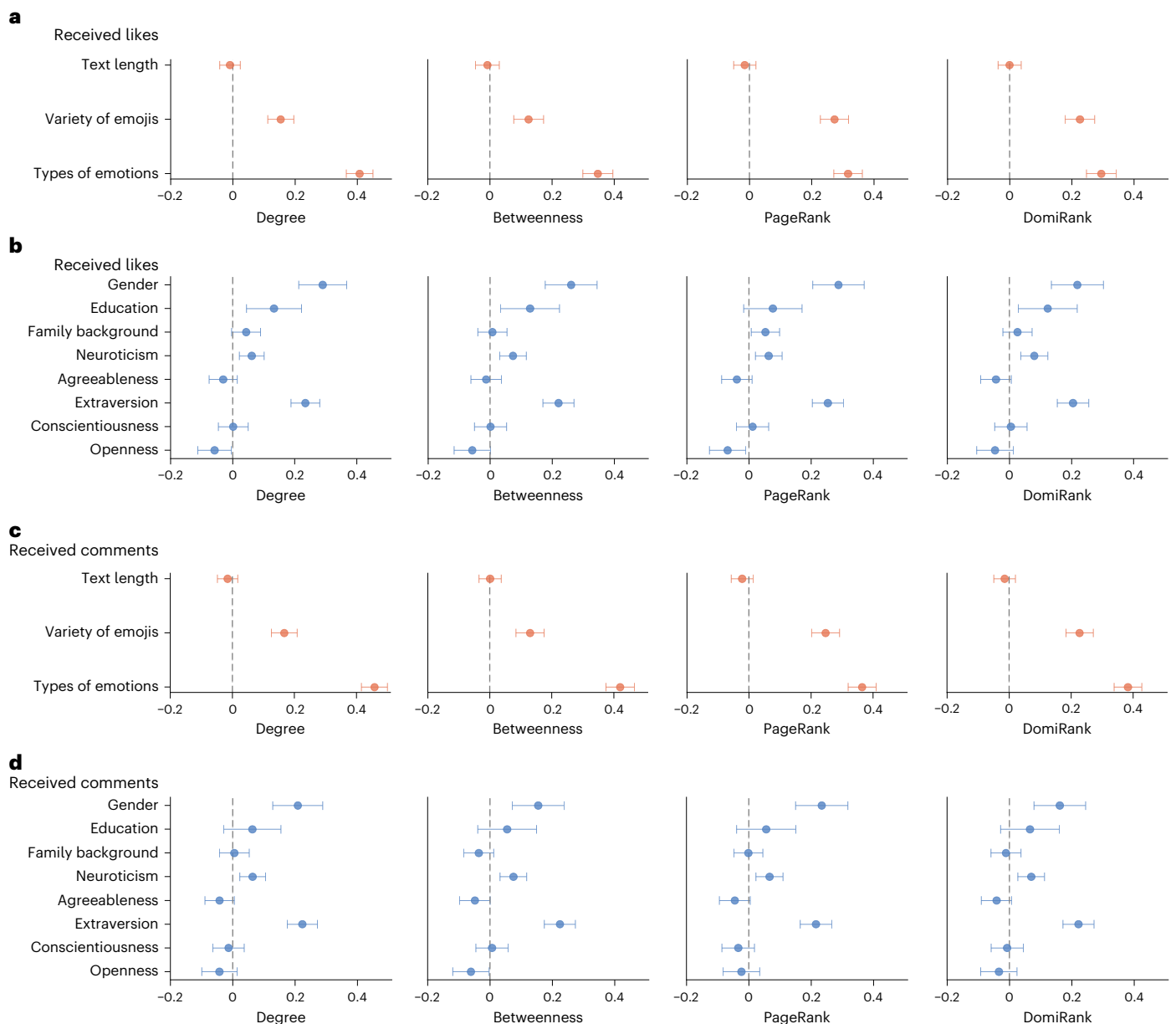


Fig. 2 | Estimated regression coefficients for each variable (with 95% confidence intervals) based on multilevel models predicting attracted attention, as measured by four centrality metrics of incoming edges. a,b, The effects of ‘how you express yourself’ indicators (a) and ‘who you are’ indicators (b) on the number of contacts from whom a user has received likes. c,d, The

effects of ‘how you express yourself’ indicators (c) and ‘who you are’ indicators (d) on the number of contacts from whom a user has received comments. In a–d, The orange lines indicate coefficients for ‘how you express yourself’ indicators and the blue lines denote coefficients for ‘who you are’ indicators. All continuous variables were standardized. $N = 2,206$.

Table 1 presents the results of the fixed-effects models, where attracted attention is measured using four centrality metrics of incoming edges (for results using alternative measurements, see Supplementary Tables 9–11). By isolating the effects of within-individual changes in the variety of emojis and types of emotions on changes in attracted attention—and accounting for time-invariant unobserved confounders—these models have offered more robust insights into the causal relationships. The results indicate that, across all models, an increase in the variety of emojis or types of emotions has a significant positive effect on attracted attention.

We also employed instrumental variable models, using the average emoji variety and average emotion types in a respondent’s middle school class (excluding the respondent) as instruments. This choice is based on the assumption that respondents’ modes of expression may be influenced by their classmates’ modes of expression,

while the attention attracted by respondents is unlikely to be directly affected by their classmates’ modes of expression. The rationale and validation of this approach are detailed in Supplementary Note 3.

Table 2 presents the model estimates from a two-stage least squares strategy, where attracted attention is measured using four centrality metrics of incoming edges (for results based on alternative measurements, see Supplementary Tables 12–14). Classmates’ mode of expression is used as an instrument to predict the respondents’ mode of expression. The results indicate that in seven out of eight models, increasing the variety of emojis (panels a and c) has a significant positive effect on attracted attention, and increasing the types of emotions (panels b and d) has a significant positive impact in all eight models.

To further corroborate the causal relationship, we conducted a series of randomized controlled trials, including both between-subjects and within-subjects designs with newly recruited participants.

Table 1 | Estimated coefficients for the variety of emojis and types of emotions based on fixed-effects models for attracted attention, measured using four centrality metrics of incoming edges

		Degree	Betweenness	PageRank	DomiRank
Panel a: received likes	Variety of emojis	0.226*** (<i>P</i> <0.001)	0.201*** (<i>P</i> <0.001)	0.248*** (<i>P</i> <0.001)	0.224*** (<i>P</i> <0.001)
	Number of observations	6,618	6,618	6,618	6,618
	Number of individuals	2,206	2,206	2,206	2,206
	Within-group <i>R</i> ²	0.100	0.062	0.072	0.077
	Types of emotions	0.444*** (<i>P</i> <0.001)	0.380*** (<i>P</i> <0.001)	0.363*** (<i>P</i> <0.001)	0.359*** (<i>P</i> <0.001)
Panel b: received likes	Number of observations	6,618	6,618	6,618	6,618
	Number of individuals	2,206	2,206	2,206	2,206
	Within-group <i>R</i> ²	0.268	0.156	0.140	0.169
	Variety of emojis	0.272*** (<i>P</i> <0.001)	0.231*** (<i>P</i> <0.001)	0.269*** (<i>P</i> <0.001)	0.278*** (<i>P</i> <0.001)
	Number of observations	6,618	6,618	6,618	6,618
Panel c: received comments	Number of individuals	2,206	2,206	2,206	2,206
	Within-group <i>R</i> ²	0.100	0.055	0.052	0.097
	Types of emotions	0.453*** (<i>P</i> <0.001)	0.341*** (<i>P</i> <0.001)	0.450*** (<i>P</i> <0.001)	0.397*** (<i>P</i> <0.001)
	Number of observations	6,618	6,618	6,618	6,618
	Number of individuals	2,206	2,206	2,206	2,206
Panel d: received comments	Within-group <i>R</i> ²	0.231	0.109	0.129	0.180

Individual characteristics (gender, highest educational level, family background and the Big Five personality traits) are time invariant in the data and are therefore differenced out during estimation. The average text length of posts is included as a control variable in all models. Within-group *R*² quantifies the proportion of the within-individual variation over time that is accounted for by the explanatory variables included in the model. The reported *P* values in parentheses are from two-sided tests of the null hypothesis that the coefficient is zero, with standard errors clustered at the school level. **P*<0.05, ***P*<0.01 and ****P*<0.001.

These experiments provide additional empirical support that increasing the variety of emojis or types of emotions has a significant positive effect on attracting attention (for details, see Supplementary Note 4).

Mechanisms underlying the effects of modes of expression on attracted attention

Given that results from the fixed-effects and instrumental variables models, as well as the randomized controlled trials, all indicate a causal relationship between mode of expression and attracted attention, we further explored the potential underlying mechanisms. Why does increasing the variety of emojis and types of emotions attract more attention? We propose three hypotheses:

Hypothesis 1 (eye-catching hypothesis): among a large number of posts, those containing emojis and negative words are more likely to catch the audience's attention. This is because emojis are visual symbols, and the human brain tends to be more sensitive to visual stimuli than to abstract text⁴⁸. In addition, the brain generally responds more strongly to negative information than to positive⁴⁹. On a social media platform where 70% of posts express positive emotions, sharing negative emotions contributes to the diversity of emotion types. Overall, both the variety of emojis and types of emotions can better capture the audience's attention, thereby increasing the level of attention directed towards certain users.

Hypothesis 2 (empathy-evoking hypothesis): among the numerous posts on social media, those that evoke emotional resonance in the audience are more likely to attract likes and comments. Different emotions always exist within a crowd. Therefore, given the same posting frequency, a more diverse emotional expression is more likely to resonate with a broader audience than a single emotional expression, thus gaining more attention. Moreover, the use of emojis

may help the audience better interpret the emotions conveyed in a post, thereby increasing the likelihood of empathy. Overall, the variety of emojis and types of emotions assist in evoking emotional resonance in a larger audience, thus attracting more attention to specific users.

Hypotheses 3.1 and 3.2 (social distance moderation hypothesis): building on the two previous hypotheses, we further consider the impact of social distance. For an individual's closest friends, attention may be attracted regardless of the mode of expression, whereas for their ordinary friends, the mode of expression may play a more decisive role. Therefore, we propose two sub-hypotheses: Hypothesis 3.1, the social distance-based eye-catching hypothesis, and Hypothesis 3.2, the social distance-based empathy-evoking hypothesis. In both cases, the eye-catching and empathy-evoking mechanisms depend on the social distance between two contacts.

We employed agent-based models (ABMs) to test the three hypotheses. The simulation process and model specifications for each hypothesis are described in the Methods. As shown in Fig. 3a, based on differences in degree distributions, ΔD , the ABM for Hypothesis 2 ($\Delta D_{\text{Hypothesis2}} = 96.15$) significantly outperforms that for Hypothesis 1 ($\Delta D_{\text{Hypothesis1}} = 153.22$; $\Delta D_{\text{Hypothesis2}} - \Delta D_{\text{Hypothesis1}} = -57.07$, $t(38) = -60.521$, $P < 0.001$, Cohen's $d = -19.139$, 95% confidence interval (CI) of mean difference (-58.98 to -55.17)), indicating that the primary mechanism by which the variety of emojis and types of emotions attract more attention is their role in evoking emotional resonance. Furthermore, considering social distance does not improve the model fit ($\Delta D_{\text{Hypothesis3.2}} = 95.51$; $\Delta D_{\text{Hypothesis3.2}} - \Delta D_{\text{Hypothesis2}} = -0.64$, $t(38) = -0.710$, $P = 0.482$, Cohen's $d = -0.225$, 95% confidence interval of mean difference (-2.46 to 1.18)), suggesting that the empathy-evoking mechanism is not related to social distance but applies equally to all contacts.

Table 2 | Estimated coefficients from the two-stage least squares regression for attracted attention, measured using four centrality metrics of incoming edges

		First stage estimation	Second stage estimation			
		Respondents' variety of emojis	Respondents' received likes			
			Degree	Betweenness	PageRank	DomiRank
Panel a: received likes	Respondents' variety of emojis		1.043*** (<i>P</i> <0.001)	0.334 (<i>P</i> =0.061)	0.398* (<i>P</i> =0.017)	0.474* (<i>P</i> =0.017)
	Classmates' variety of emojis	0.137*** (<i>P</i> <0.001)				
	First-stage <i>F</i> statistic	44.301				
		Respondents' type of emotions	Respondents' received likes			
			Degree	Betweenness	PageRank	DomiRank
Panel b: received likes	Respondents' type of emotions		0.889*** (<i>P</i> <0.001)	0.373** (<i>P</i> =0.003)	0.385** (<i>P</i> =0.001)	0.496*** (<i>P</i> <0.001)
	Classmates' types of emotions	0.198*** (<i>P</i> <0.001)				
	First-stage <i>F</i> statistic	67.404				
		Respondents' variety of emojis	Respondents' received comments			
			Degree	Betweenness	PageRank	DomiRank
Panel c: received comments	Respondents' variety of emojis		0.781*** (<i>P</i> <0.001)	0.513** (<i>P</i> =0.008)	0.522*** (<i>P</i> <0.001)	0.613*** (<i>P</i> <0.001)
	Classmates' variety of emojis	0.137*** (<i>P</i> <0.001)				
	First-stage <i>F</i> statistic	44.301				
		Respondents' type of emotions	Respondents' received comments			
			Degree	Betweenness	PageRank	DomiRank
Panel d: received comments	Respondents' type of emotions		0.747*** (<i>P</i> <0.001)	0.529*** (<i>P</i> <0.001)	0.494*** (<i>P</i> <0.001)	0.615*** (<i>P</i> <0.001)
	Classmates' types of emotions	0.198*** (<i>P</i> <0.001)				
	First-stage <i>F</i> statistic	67.404				

The first-stage estimates represent the coefficients of the instrumental variables (classmates' modes of expression) in predicting the endogenous variables (respondents' modes of expression). The second-stage estimates show the coefficients of the predicted values of the endogenous variables on the dependent variable (attracted attention). Individual characteristics (gender, highest educational level, family background and the Big Five personality traits) and the average text length of posts are included as control variables in all models. The reported *P* values in parentheses are from two-sided tests of the null hypothesis that the coefficient is zero, with standard errors clustered at the school level. **P*<0.05, ***P*<0.01 and ****P*<0.001. *N*=2,206.

We also used network density to evaluate the simulation results. Figure 3b shows the network densities of 26 subnetworks, comparing the simulated networks with the real network. The figure demonstrates that, among all the hypotheses, the ABM for Hypothesis 2 (overall network density = 5.52×10^{-4}) produced results most closely matching those of the real network (overall network density = 6.10×10^{-4}), reaffirming the explanatory power of the empathy-evoking mechanism, regardless of social distance between contacts.

The disparities and varying effects of the mode of expression among different groups

Since the variety of emojis and types of emotions were identified as having a significant effect on gaining attention on social media, we further examined variations in its impact among different groups. The sample was divided into different groups based on individual characteristics: gender (males versus females), highest educational level (below college versus college and above), family background (low versus high parental socioeconomic status) and Big Five personality traits (lower 50% versus upper 50% in each dimension).

We first examined the correlation coefficients between individual characteristics and the two dimensions of expression. No correlation

or only weak correlations (*r* < 0.3) were found between the examined sociodemographic attributes or personality traits and the variety of emojis and types of emotions. Figure 4a,d shows that the explanatory power of each characteristic for the two dimensions of expression is also small (marginal *R*² < 8% in multilevel models; for further details, see Supplementary Table 8). Additional analysis showed that the overall explanatory powers of all individual characteristics were around 10.3% and 6.0% for the two dimensions of expression, respectively, leaving most variations unexplained. These results suggest that the mode of online expression is not determined by sociodemographic attributes or personality traits. Instead, how one expresses oneself is largely independent of who one is.

Figure 4b,e illustrates the disparities between the two dimensions of expression in different groups. In particular, the figures show that individuals with different genders, family backgrounds and personality traits of neuroticism and extraversion display significant differences in their modes of expression. However, all the differences fall within 0.5 s.d. of the overall mean values of variety of emojis and types of emotions, supporting the notion that belonging to a group based on these characteristics is not strongly predictive of how one expresses oneself online. Figure 4c,f illustrates the marginal

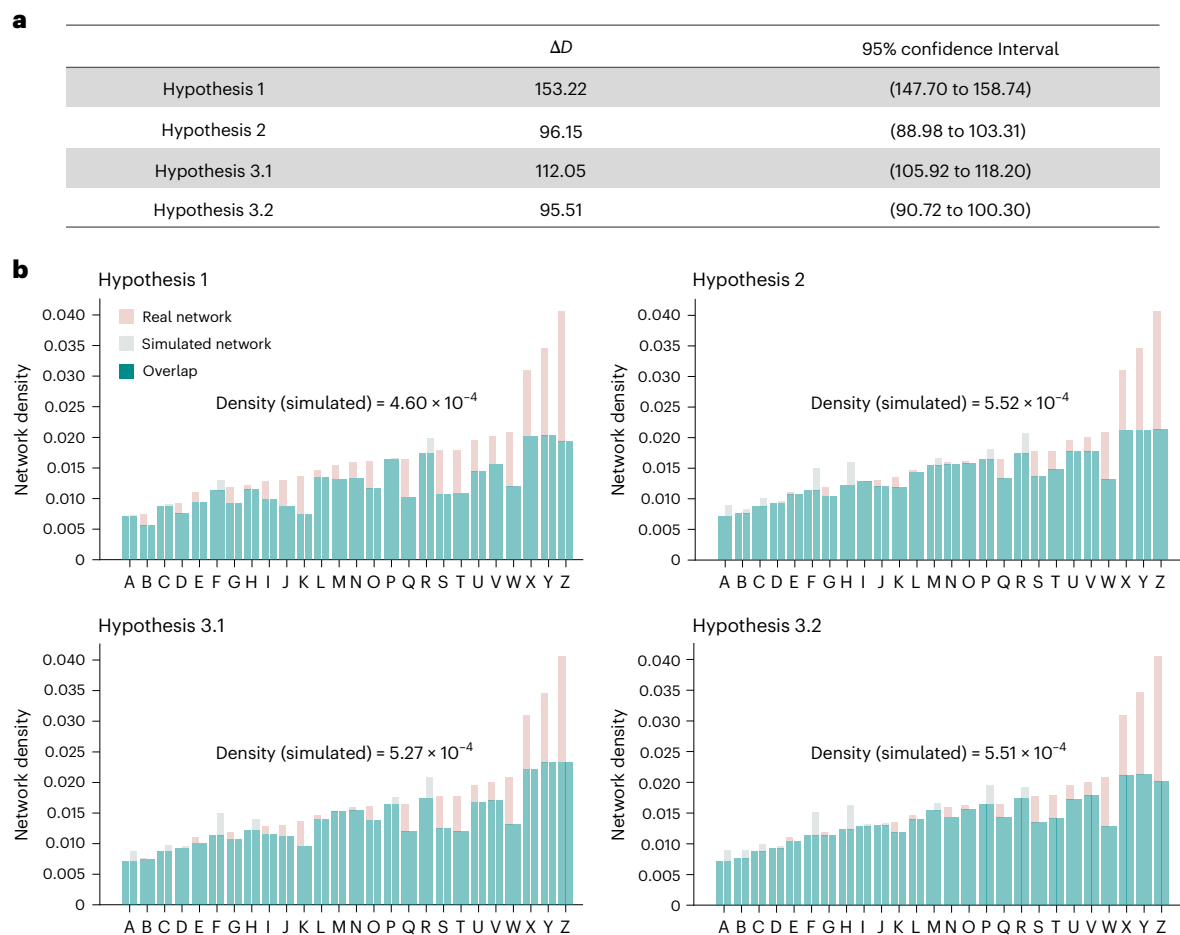


Fig. 3 | Comparison of degree distributions and network densities between the simulated and real networks. a, The difference in degree distributions between the simulated networks and the real network. ΔD represents the difference in degree distributions, with 95% confidence intervals derived from 20 simulation

runs. **b,** Comparisons of network densities between the simulated networks and the real network. Simulations were conducted separately for 26 subnetworks (A–Z) and then aggregated for comparison.

effects of increasing the variety of emojis and increasing types of emotions: both show a significant positive association with attracting attention across all groups. Moreover, increasing the variety of emojis has a greater marginal effect on males and people with at least a college-level education than it does on their counterparts. In Fig. 4, attracted attention is measured by degree centrality based on incoming edges of received likes. Supplementary Figs. 15 and 16 include results based on alternative measurements.

Is the attention from highly appealing expressions lasting?

We combined the variety of emojis and types of emotions to define users who ranked in the top 50% in both dimensions as ‘high-appeal presenters’, those in the bottom 50% in both dimensions as ‘low-appeal presenters’ and those in the top 50% in one dimension and the bottom 50% in the other as ‘middle-tier presenters’. We examined to what extent modes of expression vary over time and, for those who transitioned from high-appeal to low-appeal presenters or vice versa, whether their attractiveness was maintained or changed accordingly.

As shown in Fig. 5, most users in the cross-sectional data of the first and second years in our observation window (Figs. 5a,c) are labelled as either high-appeal or low-appeal presenters, leaving only a small fraction of the overall sample as the middle-tier group. This suggests that while using emojis and conveying emotions are differing dimensions of online expression with independent effects on grabbing attention on social media, they also share some similarities and exert a combined force in shaping individual expression.

When we compare the modes of expression in the first and second years (Fig. 5a), we observe that approximately 69% of high-appeal presenters and 69% of low-appeal presenters maintained those modes over time. Around 17% and 15% of high- and low-appeal presenters, respectively, transitioned into the middle-tier group, and around 14% of high-appeal and 16% of low-appeal presenters transitioned into the opposite group. The passage from the second year to the third year included more of those who maintained their position as high- or low-appeal presenters and less of those who transitioned: over 71% and 77% of high- and low-appeal presenters, respectively, maintained their modes of expression, whereas only around 9% in each group changed to the opposite one (Fig. 5c). This suggests that most social media users tend to maintain their modes of expression over time.

For those who made changes in their modes of expression, their attracted attention changed accordingly. Figure 5 uses degree centrality based on incoming edges of received likes as an example. Fig. 5b,d shows that whether users shifted their modes of expression from the first year to the second or from the second to the third, transitioners from the high-appeal to the low-appeal group ended up with a significantly decreased likelihood of entering the top quartile of attractiveness compared with the stable high-appeal group. Moreover, their likelihood of falling into the bottom quartile increased significantly. By contrast, transitioners from the low-appeal to the high-appeal group were significantly more likely to enter the top quartile and less likely to fall into the bottom quartile than the

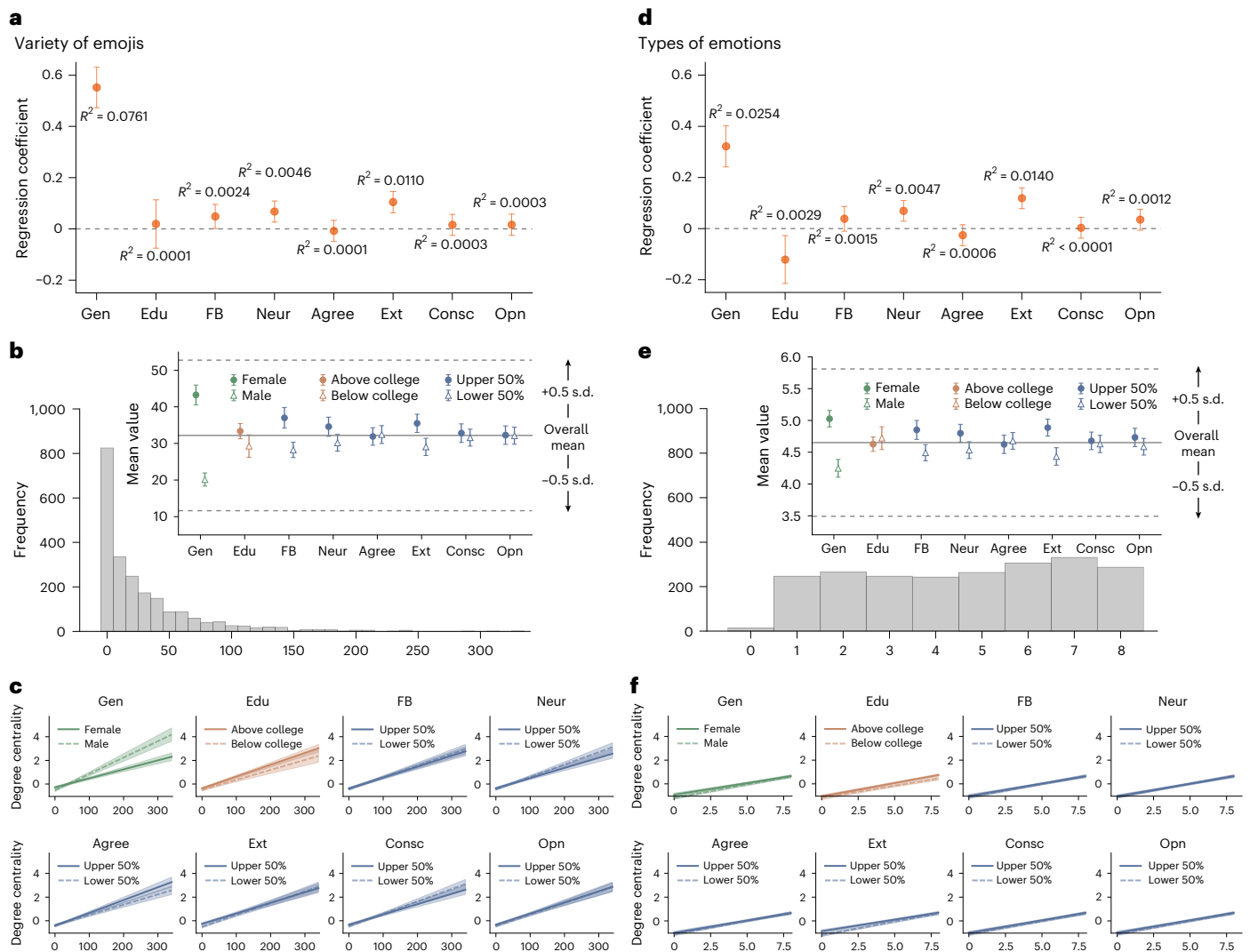


Fig. 4 | Associations between individual characteristics and modes of expression and the distribution and marginal effects of expression modes among different groups. a, d. The estimated regression coefficients (with 95% confidence intervals) from multilevel models predicting the variety of emojis (a) and types of emotions (d) by different individual characteristics. The explanatory power (marginal R^2) of each characteristic is indicated. **b, e.** The distributions of variety of emojis (b) and types of emotions (e). Insets: overall mean values with ± 0.5 s.d. and their group mean values with 95% confidence

intervals of the two dimensions of expression among different groups. **c, f.** The marginal effects of increasing variety of emojis (c) and types of emotions (f) on enhancing attractiveness for different groups, using degree centrality based on incoming edges of received likes as an example. The lines represent predicted marginal effects from multilevel models, with shaded areas indicating 95% confidence bands. Agree, agreeableness; Consc, conscientiousness; Edu, highest educational level; Ext, extraversion; FB, family background; Gen, gender; Neur, neuroticism; Opn, openness. $N = 2,206$.

stable low-appeal group. This indicates that social media users may enhance attention by employing high-appeal expressions, but the attention induced by highly appealing expressions cannot last if this mode of expression changes. Notably, alternative measures of attracted attention reveal similar results (for more details, see Supplementary Figs. 17 and 18).

We further investigated the impact of attracted attention on respondents' life satisfaction and subjective wellbeing. The most recent survey in the China Education Panel Survey series was conducted from September 2019 to April 2020. First, we extracted the exact date each respondent participated in the survey and reported their life satisfaction and subjective wellbeing. Next, we calculated the attracted attention of each respondent in the 90 days before their interview date. Using the incoming edges of received likes as an example—that is, the number of contacts who 'liked' the respondent's posts in the 90 days before the interview—we found that attracted attention had a significant positive effect on both life satisfaction (standard coefficient

$\beta = 0.042$, 95% CI (0.004 to 0.080), $P = 0.031$) and subjective wellbeing ($\beta = 0.094$, 95% CI (0.009 to 0.180), $P = 0.031$), even after controlling for personal characteristics (for details, see Table 3). By integrating online and offline information, this finding highlights the importance of attention capital for individual wellbeing in the digital era.

Discussion

In a digital age characterized by the increasing prominence of attention capital, who stands a better chance of acquiring it? Does the allocation of attention capital extend the advantages of groups who are privileged in offline spaces into online ones? Using an online and offline integrated dataset for a national representative sample, we examined the mechanisms underlying the allocation of attention capital. Our analyses revealed that for the vast majority of social media users, 'how you express yourself' is more important than 'who you are'. Those from privileged family background or with advantages

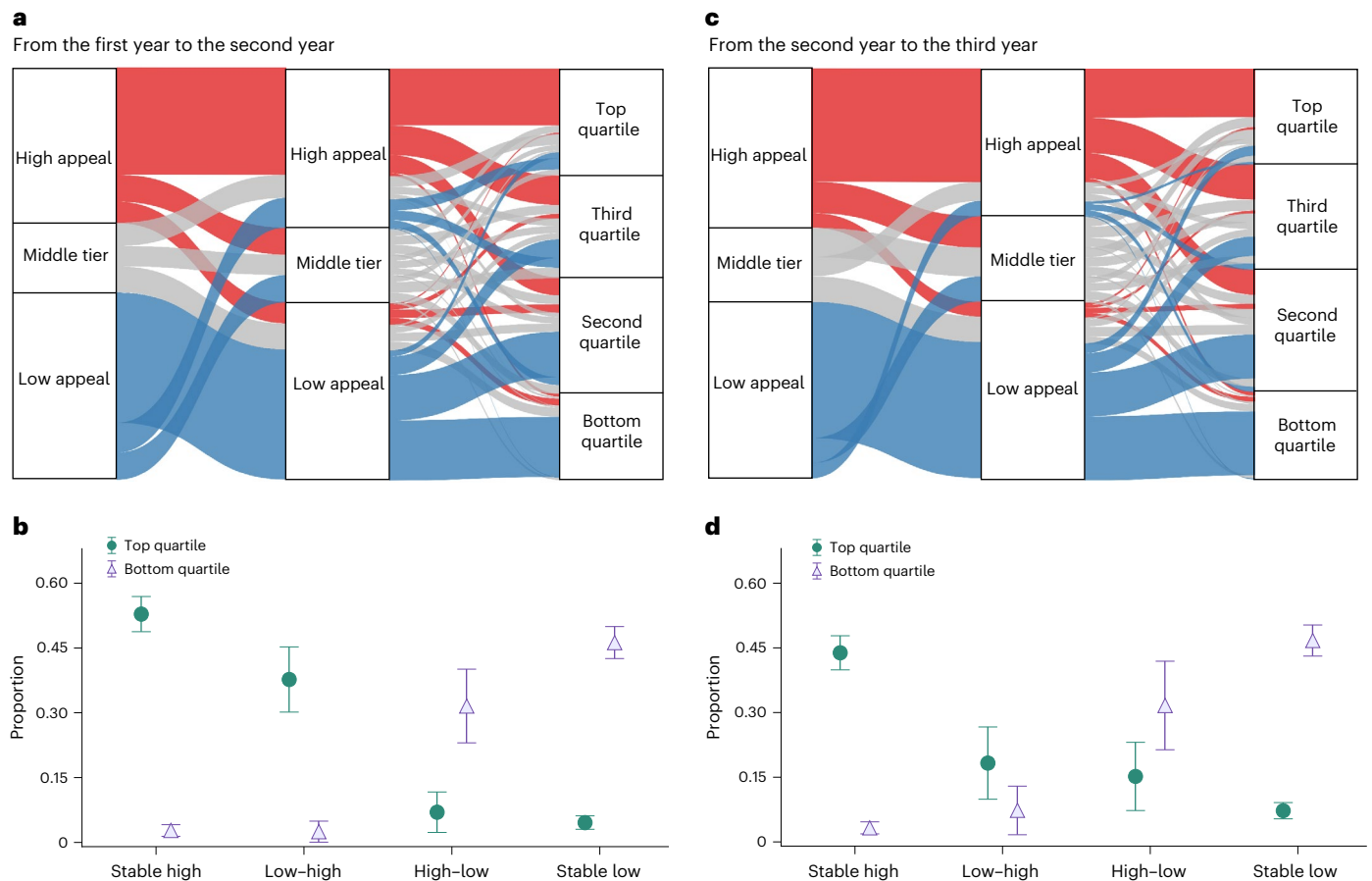


Fig. 5 | Changes over time in modes of expression and their impact on attracted attention, as measured by incoming edges of received likes. a, Changes in modes of expression from the first year to the second year of observation and the impact on attracted attention in the second year. **b**, The likelihood of entering the top quartile and bottom quartile of attractiveness across four groups of users (stable high-appearance presenters, high-to-low transitioners, low-to-high transitioners and stable low-appearance presenters) in the second year. **c**, Changes in modes of expression from the second year to the third year of observation and

the impact on attracted attention in the third year. **d**, The likelihood of entering the top quartile and bottom quartile of attractiveness across four groups of users (stable high-appearance presenters, high-to-low transitioners, low-to-high transitioners and stable low-appearance presenters) in the third year. In **a** and **c**, the total height of the diagram indicates the overall sample and the height of each arc represents the percentage of the overall sample transitioning from one category to another. In **b** and **d**, the error bars indicate 95% confidence intervals around the sample proportions. $N = 2,206$.

in human capital may not stand a better chance of obtaining attention capital in cyberspace. Instead, certain modes of expression exert a more decisive impact. Our study confirmed the causal effect of modes of expression on attracted attention and identified empathy evocation as the primary underlying mechanism.

The findings add new evidence to the discussion about whether the allocation of attention capital aligns with meritocratic logic^{50,51}. Our results suggest that while sociodemographic backgrounds have an impact, they are not the key distinguishing factors in the acquisition of attention capital. We consider this to illustrate the first characteristic that describes how attention capital is distributed in the general population: its low alignment with existing resources. In the digital age, this feature of attention capital may sustain a multidimensional stratification system and avoid status crystallization or winner-takes-all scenarios. However, we acknowledge that circumstances may still evolve. For example, in line with the scarcity of attention capital, the exacerbation of information overload may make competition more intense⁵², meaning that it is increasingly difficult to acquire attention capital. Whether this may favour privileged groups and lead to high coherence between attention capital and other resources is a worthwhile issue for future research.

Among the modes of expression examined in this study, we found that the use of various emojis and the expression of emotions are both

crucial to attracting attention and are largely independent of users' sociodemographic attributes and personal traits. Our finding that a mode of expression is not exclusive to any particular group means that a person would not require extensive training to acquire it. Anyone in the digital age may easily adopt a highly appealing expression to gain more attention, leading to considerable manipulability in the allocation of attention capital. Moreover, while previous studies have focused more on the role of negative emotions^{53–56}, we found that diverse emotional expressions are more attractive on social media platforms such as WeChat, where updated posts are, in most cases, only visible to verified friends. Therefore, within an acquaintance network, excessive negative or positive emotions may fail to increase popularity if such expressions do not contribute to greater diversity in the emotion types displayed by users.

Regarding whether the attention from highly appealing expressions can last, most participants in our sample were found to maintain a certain mode of expression over time, but for those who made substantial changes, their attracted attention changed accordingly. These findings suggest that attention capital has a weak attachment to individuals. Unlike other types of capital, which may be difficult to obtain but easy to maintain (for example, education attainment and occupational prestige), attention capital seems easy to obtain but difficult to maintain. Attracting more attention may not be a difficult

Table 3 | Estimated coefficients of incoming edges of received likes in the 90 days before the interview on life satisfaction and subjective wellbeing, based on multilevel models

	Life satisfaction	Subjective wellbeing
Incoming edges of received likes in the 90 days before the interview	0.042*	0.094*
	(<i>P</i> =0.031)	(<i>P</i> =0.031)
Gender (reference male)	-0.066	0.311***
	(<i>P</i> =0.088)	(<i>P</i> <0.001)
Education (reference below college)	0.189***	0.269**
	(<i>P</i> <0.001)	(<i>P</i> =0.005)
Family background	0.020	0.165***
	(<i>P</i> =0.306)	(<i>P</i> <0.001)
Extraversion	0.109***	0.044
	(<i>P</i> <0.001)	(<i>P</i> =0.407)
Openness	0.057*	0.090
	(<i>P</i> =0.036)	(<i>P</i> =0.141)
Agreeableness	0.071**	0.154**
	(<i>P</i> =0.002)	(<i>P</i> =0.003)
Conscientiousness	0.207***	0.150**
	(<i>P</i> <0.001)	(<i>P</i> =0.006)
Neuroticism	-0.233***	-0.387***
	(<i>P</i> <0.001)	(<i>P</i> <0.001)
Number of individuals	2,206	2,206
Number of schools	111	111

All continuous variables, including life satisfaction, incoming edges of received likes in the 90 days before the interview, family background and the Big Five personality traits, were standardized. A multilevel linear regression model was used to estimate life satisfaction, while a multilevel ordered logit regression model was employed to estimate subjective wellbeing, an ordered variable ranging from 1 to 5. The reported *P* values in parentheses are from two-sided tests of the null hypothesis that the coefficient is zero. **P*<0.05, ***P*<0.01 and ****P*<0.001.

prospect, but the advantage afforded by attention capital is not a stable status that can be attained once and forever. Instead, it requires continuous input and frequent upkeep, and high-appeal expressions seem important in these processes.

Overall, the three characteristics we identified—low alignment with existing resources, considerable manipulability and ease of acquisition but difficulty in sustaining over time—jointly contribute to an initial outline of the allocation of attention capital among general users of social media platforms. Along with demonstrating the causal effect of modes of expression on attracted attention and identifying empathy evocation as a primary underlying mechanism, this study offers a more nuanced and comprehensive perspective on the allocation of attention capital, providing new insights into resource allocation and operational logic in the digital era.

While WeChat's widespread use, absence of fake followers and minimal algorithmic intervention make it an ideal case for studying attention gained among general users, these characteristics also contribute to its uniqueness compared with other platforms. To assess the generalizability of our findings, we conducted an additional analysis using an open-access dataset from Twitter (now X). Unlike WeChat, Twitter facilitates attention competition beyond existing social networks, allowing users to reach a broader audience. This environment may foster the emergence of social media stars, incentivize profit-driven behaviours such as purchasing fake followers and be influenced by algorithmic recommendation systems. Despite these differences, our analysis yielded highly similar results,

providing cross-platform support for our findings. However, the Twitter dataset lacks information on personal characteristics, preventing a direct comparison between the effects of 'who you are' versus 'how you express yourself'. Future research could explore this further and extend the analysis to other social media platforms.

Future research may also broaden the scope of this study in two additional directions. First, the majority of respondents in our survey were aged 17–21 years and most had not yet entered the job market at the time of data collection. Whether our results would differ for other age groups, particularly older ones, remains unknown (for further discussion, see Supplementary Note 5). Second, the dataset includes only posts and below-post interactions that the research team was authorized to access, excluding content with privacy restrictions. While posts intended for communication with specific contacts rather than attracting broader attention were not the primary focus of this study, future research could explore how content visibility settings affect the mechanisms of attention allocation.

In summary, using a nationally representative dataset that integrates online and offline information, we identified three key characteristics of how attention capital is allocated among general users and revealed the mechanism through which modes of expression influence attention attraction. Our findings suggest that the allocation of attention capital differs notably from that of traditional forms of capital, with important implications for social stratification and individual wellbeing in the digital age. We argue that the acquisition and allocation of attention capital should become a central focus of social science research in the digital era, and that the architecture of social media platforms—which affects the visibility of different users—needs to be considered not only from a profit perspective but also from the standpoint of promoting digital equity.

Methods

Data

We used a dataset that links a nationally representative panel survey in China (China Education Panel Survey) to the survey respondents' social media records. The nationwide survey began in 2013 and employed a probability proportionate to size sampling method. Its smallest sampling unit was the class and all students in the sampled classes were enrolled in the survey, except for several students who were absent at the time of data collection. Ultimately, the survey included 10,279 grade 7 students (mostly aged 12–13 years) from 221 classes at 112 schools across China, with a response rate of 99.16%. After the baseline survey (wave 1), four more follow-up survey rounds were conducted in 2014, 2015, 2017 and 2019 (waves 2–5). The average attrition rate of the follow-up surveys was 6.47%.

In 2018, when the majority of respondents were aged 17–18 years, we sought their permission to access their online posts and interactions with their middle school classmates on WeChat, the largest social media platform in China with ~1.4 billion monthly active users⁴⁰. A total of 8,636 out of 10,279 (84.02%) respondents granted us permission. We constructed an online network of these respondents, using 1,048,999 online posts and 1,030,710 inner-circle interactions collected from May 2018 to April 2021, when most respondents were in the 17–20 or 18–21 year age groups.

From these 8,636 respondents, we randomly selected half (*N*=4,318) and requested permission to link their WeChat activities to their offline survey data. In the invitation, we outlined the purpose of the study, the potential risks of participation, and the methods for protecting personal information (for example, the data linkage would be managed by designated personnel, all the researchers would sign confidentiality agreements, all the information would be stored on encrypted servers and the data would be used solely for scientific research).

Of the 4,318 respondents to whom we sent the request to link their WeChat activities with their offline survey data, a total of 2,703 respondents (62.60%) provided informed consent. After applying

listwise deletion to cases with missing values on key variables, 2,206 respondents were included in the final analytical sample. Compared with the overall sample ($N = 10,279$), this subsample ($N = 2,206$) was largely random as the distributions of most (not all) demographic variables did not differ significantly from the overall sample. As a robustness check, we generated a weight parameter (for details, see 'Analysis'). The subsample had the same covariate distributions as the whole sample after weighting, and the weighted results were similar to unweighted ones (for details, see Supplementary Table 15 and Supplementary Figs. 19–22).

Ethics statement

For the analysis based on the China Education Panel Survey, ethical approval was obtained from the Ethics Committee of the National Survey Research Center at Renmin University of China (reference nos. RN2012042201 and RN2018041101). All participants included in the analysis provided informed consent to participate and to allow their survey responses to be linked with social media data. For the supplementary randomized controlled trials, ethical approval was granted by the Science and Technology Ethics Committee at Tsinghua University (project no. THU-04-2025-1007). Informed consent was obtained from all participants, and the study was conducted in accordance with the relevant guidelines of the Declaration of Helsinki.

Measures

Indicators for node centrality. As mentioned in 'Results', we used four metrics to measure node centrality: degree centrality, betweenness centrality, PageRank centrality and DomiRank centrality. Among these metrics, degree centrality⁵⁷, which indicates the number of neighbours directly connected to a node, is one of the most widely used metrics. Betweenness centrality measures the extent to which a node lies on the shortest paths between two other nodes in the network. PageRank⁵⁸ and DomiRank⁵⁹ centralities account for the importance of a node's neighbours. PageRank was originally proposed to measure the relative importance of web pages and assign higher centrality to nodes if other important nodes connect to them. Compared with PageRank, DomiRank integrates both local and global topological information when identifying nodes of high importance. Given their right-skewed distributions, we applied a logarithmic transformation to all centrality measures in the subsequent analysis. All centrality metrics were standardized to have a mean of 0 and a standard deviation of 1.

Indicators for 'how you express yourself'. We used three indicators to measure the modes of expression: the average text length of posts, the variety of emojis and types of emotions. The average text length of posts was the average count of Chinese characters for all posts published by a user in a period. The variety of emojis was determined by the number of unique emojis a user ever employed in their online posts during a period. To measure types of emotions, we first categorized the predominant emotion of each post into one of the eight basic emotion types (anticipation, anger, disgust, joy, sadness, surprise, fear and trust)^{60,61} with the assistance of a locally deployed large language model. After training, the annotation accuracy of the large language model for each of the eight emotion types ranged from 0.93 to 0.99, as measured by the *F1* score. We then generated the variable of types of emotions by traversing all posts and counting their emotion type labels for each user in a period. Further details are provided in Supplementary Notes 1 and 2. All indicators were standardized for model estimation.

Indicators for 'who you are'. We used the following individual characteristics as indicators for 'who you are': gender, highest educational level, family background and the Big Five personality traits. We treated gender as a dichotomous variable and coded female as '1' and male as '0'. The highest educational level was also dichotomously recoded into college and above ('1') and below college ('0'). To indicate family

background, we employed parental socioeconomic status, a continuous variable generated from principal component analysis and based on parents' highest occupation level, highest education level and annual household income. The Big Five personality traits were generated from a brief version of the Chinese Big Five Personality Inventory with 40 items⁶², and a summary score was generated for each dimension: extraversion, openness, agreeableness, conscientiousness and neuroticism. All indicators in this group were based on information from the offline survey, and all continuous variables were standardized in model estimation. The descriptive statistics for the above indicators are presented in Supplementary Table 7.

Analysis

We used Stata 18 for data cleaning, R 4.3.1 for data analysis, Python 3.11.7 for both data analysis and visualization and NetLogo 6.4.0 for simulation. The code for data processing and all related analyses, as detailed below, is publicly available.

Network robustness analysis. We examined how the relative size of the largest connected component (LCC) changed with nodes removed sequentially in descending order of centrality scores to assess the impact of key nodes identified by different node centrality metrics on network robustness^{59,63}. As nodes were removed from the network, the size of LCC decreased, indicating a lower level of connectivity. At a given fraction of removed nodes, a faster decline in the size of LCC indicated that the removed nodes played a more important role in maintaining network robustness. We determined which centrality metric was more effective at identifying key nodes for network robustness by comparing the changes in the relative size of LCC.

SIR model. The susceptible–infected–recovered (SIR) model was proposed in epidemiology to understand how infectious diseases spread and has been widely applied to examine social spreading processes^{64,65}. In this study, we considered likes or comments as a manifestation of being reached or influenced by the information source and employed the SIR model to compare the influence of key nodes in the social spreading process, during which the top 0.01% most influential nodes were identified based on different node centrality metrics. We then calculated the final affected scale following the spreading process, using those influential nodes as initial spreaders. In this way, we compared which centrality metric was more effective at detecting influential nodes in the network. We set the affected rate to 0.4 and the recovered probability to 1 in the SIR simulations, and the results were averaged over 500 independent runs.

Multilevel model. We used multilevel models to examine how the modes of expression and individual characteristics affect attractiveness given the hierarchical structure of the dataset. As individuals are nested within schools, the model specification is as follows:

$$Y_{is} = \beta_0 + \sum_{j=1}^n \beta_j X_{jis} + \alpha_s + \varepsilon_{is} \quad (1)$$

where β_0 and β_j are parameters to be estimated, Y_{is} is the attracted attention of the i th individual from the s th school. X_{jis} is the value of the i th individual from the s th school for the j th predictive variable from either the 'how you express yourself' group or the 'who you are' group; α_s is the school-specific effect, which follows a normal distribution with a mean of 0 and a variance of σ_α^2 , whereas ε_{is} is the individual-specific effect from a normal distribution with a mean of 0 and a variance of σ_ε^2 . Following the approach proposed by Nakagawa and Schielzeth⁴¹, we calculated marginal R^2 to assess the explanatory power of the predictive variables. For more details, see 'Results'. We also calculated the conditional R^2 for the explanatory power of the entire model, including the contribution of random effects, as shown in Supplementary Fig. 6.

Fixed-effects model. To identify the causal relationships between the mode of expression (that is, the variety of emojis and types of emotions) and attracted attention, we employed fixed-effects models. We calculated both the mode of expression and attracted attention on an annual basis: May 2018–April 2019, May 2019–April 2020 and May 2020–April 2021. Each variable was standardized to have a mean of 0 and a standard deviation of 1. Hausman tests indicated that fixed-effects models were preferred over random-effects models. The model specification is as follows:

$$Y_{it} = \beta_0 + \beta_1 \text{expression}_{it} + \mu_i + \varepsilon_{it} \quad (2)$$

where Y_{it} represents the attracted attention of individual i in year t ; expression_{it} refers to the variety of emojis or types of emotions in the posts of individual i in year t , μ_i represents the unobserved, time-invariant factors specific to each individual, and ε_{it} is the error term. The standard errors of the regression coefficients were clustered at the school level to account for potential autocorrelation and heteroskedasticity.

Instrumental variables model. In addition to fixed-effects models, we employed instrumental variables models to examine the causal effect of the mode of expression on attracted attention. We used the average value of the variety of emojis and types of emotions in a respondent’s middle school class (excluding the respondent) as instruments. While an individual’s mode of expression can be influenced by their peer group’s mode of expression, the attention they attract depends on their own posts and is unrelated to their classmates’ posts, as supported by our data. The rationale and validation of this approach are discussed in Supplementary Note 3.

To estimate the instrumental variables models, we employed a two-stage least squares technique. The models are specified as follows:

$$X_i = \gamma_0 + \gamma_1 Z_i + \varepsilon_{it} \quad (3)$$

$$Y_i = \beta_0 + \beta_1 \hat{X}_i + v_{it} \quad (4)$$

In the first stage, we regressed the potential endogenous variables X_i (that is, the variety of emojis or types of emotions) on the instrumental variables Z_i , as shown in equation (3), and generated the predicted values \hat{X}_i . In the second stage, we replaced X_i with the predicted values from the first stage (\hat{X}_i), as shown in equation (4), and estimated the outcome variable Y_i .

Agent-based model. In the agent-based modelling approach, each agent represents an individual actor using the social media platform, and r_i is the likelihood that an agent will post within a given time unit. Each post is represented by an occupied patch, which contains information about the main emotion type of the post and the variety of emojis it contains. The posts disappear after a scheduled duration, simulating the transient nature of most social media posts in terms of capturing the audience’s attention.

When an agent publishes a post (that is, occupies a patch), an emotion type and a variety of emojis are assigned to the patch. These two values are drawn from the agent’s real-world behaviours. The likelihood that the post expresses a positive, negative or neutral emotion depends on the proportions of different emotions that appear in the agent’s real posts over the 3 years observation window, and the variety of emojis is chosen from the real list of the emojis the agent used in each post they published. When an agent encounters another agent’s posts, the likelihood that they are experiencing positive, negative or neutral emotions at that moment is set to 5:2:1, which reflects the general pattern of emotional experience in daily life⁶⁶.

In this study, as over 99% of interactions occurred within 26 sub-networks, the simulation process was conducted separately within each subnetwork. Based on the initial settings, the simulation process followed these steps in each subnetwork:

Step 1. Agent movement: each agent randomly moved one step to a new patch.

Step 2. Decision to post: if the patch was unoccupied, the agent needed to decide whether to occupy it (that is, publish a post), which was determined by parameter r_i . If the agent chose to post, the emotion type and variety of emojis for the post were randomly assigned based on the agent’s real-world behavioural records.

Step 3. Decision to interact with an existing post: if the patch was already occupied, the agent needed to decide whether to engage with the existing post. The probability of engagement followed a function specified for each hypothesis (see below). If the agent chose to engage with the post, an incoming edge would be created for the post’s owner if no such edge existed.

Step 4. End of simulation: after each movement, every occupied patch was checked to see if it exceeded the scheduled duration. If it did, the post disappeared, the patch returned to an unoccupied status and it could be occupied again. Meanwhile, the accumulated number of posts was calculated. If the number was smaller than the overall number of real posts published in the subnetwork over the 3 years, a new round of the simulation process began from Step 1. The simulation did not stop until the accumulated number reached or exceeded the benchmark of the real posts in the subnetwork.

The model specifications for the three hypotheses are as follows:

Hypothesis 1 (eye-catching hypothesis): according to this hypothesis, the more types of emojis a post contains, the higher the probability that the post will catch the audience’s attention. In a context with more positive emotions, posts expressing negative emotions are considered more eye catching. Based on this mechanism, the probability that an audience member’s attention is directed to a post is specified as follows:

$$f = t(1 - e^{-\beta Z}) + (1 - t)b(1 - R^\alpha), \quad (5)$$

where t is a weight parameter ranging from 0 to 1, indicating the salience of the variety of emojis in attracting attention and $(1 - t)$ signifies the relative importance of types of emotions. Z represents the variety of emojis that an actor may use in a post, which is a non-negative integer randomly drawn from the actor’s real posts; b is a binary variable indicating whether the post expresses negative emotion; R is a time-varying parameter representing the proportion of negative posts in the given context; α and β are non-negative parameters, and t , α and β are parameters that require optimization in the simulation process.

Hypothesis 2 (empathy-evoking hypothesis): according to this hypothesis, the probability that an audience member ‘likes’ or comments on a post depends on the extent to which they resonate with the emotion of the post and the use of emojis increases the likelihood of empathy. The equation is specified as follows:

$$f = 1 - \left(\frac{d_{\text{emo}}}{4}\right)^\gamma e^{-\delta Z}, \quad (6)$$

where d_{emo} is the distance between the expressed emotion in the post and the specific emotion of an audience member when browsing the post. This is a non-negative integer ranging from 0 to 4, based on the relationship between the eight basic emotion types⁵⁵. Z represents the variety of emojis in the post. γ and δ are parameters that need to be optimized in the simulation process.

Hypotheses 3.1 and 3.2 (social distance moderation hypothesis): based on equations (5) and (6), we further consider the influence of social distance. The equations for Hypothesis 3.1 (social distance-based

eye-catching hypothesis) and Hypothesis 3.2 (social distance-based empathy-evoking hypothesis) are as follows:

$$f = [t(1 - e^{-\beta z}) + (1 - t)b(1 - R^\alpha)] \frac{d}{d+1} + \frac{1}{d+1} \quad (7)$$

$$f = \left[1 - \left(\frac{d_{\text{emo}}}{4} \right)^y e^{-\delta z} \right] \frac{d}{d+1} + \frac{1}{d+1}. \quad (8)$$

In both equations, d is a positive parameter indicating the social distance between two contacts and the other parameters have the same meanings as in equations (5) and (6). When the social distance between two contacts is substantial, the probability of an audience member's attention being directed to a post is primarily determined by the social media user's mode of expression. Conversely, when the social distance between two contacts is small, the mode of expression no longer plays a key role in allocating the audience's attention.

Under different hypotheses, the simulation process generates distinct networks based on the incoming edges. By comparing the simulated networks with the real network, we can determine which hypothesis best represents the underlying mechanism that aligns most closely with reality. The difference between the simulated and real networks is measured by the difference in their degree distributions. This is calculated as the square root of the sum of squared differences between the incoming edges of nodes in the two networks, with the incoming edges sorted in ascending order. The equation is as follows:

$$\Delta D = \sqrt{\sum_{i=1}^N \left(k_i^{(\text{sim})} - k_i^{(\text{real})} \right)^2}, \quad (9)$$

where ΔD represents the difference in degree distributions, N is the total number of nodes in the network (8,636), $k_i^{(\text{sim})}$ and $k_i^{(\text{real})}$ are the incoming edges of the i th node in the simulated and real networks, respectively, after sorting the incoming edges of all nodes in ascending order. To further evaluate the hypotheses, we employed the Kolmogorov–Smirnov test to examine whether a specific mechanism was significantly better than another in explaining the effect of the mode of expression on attracted attention.

Weighting procedure. We implemented a weighting procedure using an iterative proportional fitting method⁶⁷ that iteratively calibrates the distribution of key parameters such that they correspond to those of the overall sample. After the weighting process, the analytical sample has the same covariate distributions as the overall sample. We repeated all steps in our analysis after applying the weight parameter, and these results were similar to the unweighted ones (for details, see Supplementary Figs. 19–22).

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability

The data supporting the main findings of this study are available from the corresponding authors upon request, subject to compliance with the laws of the People's Republic of China and approval from the Office of Research at Renmin University of China. The data are not publicly available due to their sensitive nature and the potential for identification, which could compromise research participant privacy.

Code availability

The code used for data processing and analysis is available from the corresponding authors upon request and subject to the necessary data access approvals.

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Author contributions

Y.Z. conceived the study and wrote the paper. Y.Z., T.Q. and W.W. jointly designed the analytical framework. W.W. was responsible for data collection and dataset construction. Y.Z., T.Q., Y.C., M.K., W.B., Y.Y., X.H. and W.L. performed the data analyses. All authors contributed to reviewing and approving the final version of the paper.

Competing interests

The authors declare no competing interests.

Additional information

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Data collection	The China Education Panel Survey (CEPS) data were collected using a self-administered paper-and-pencil questionnaire for Wave 1 to Wave 3, and LimeSurvey for Wave 4 and Wave 5. The WeChat data were obtained through daily manual backups. In addition, we conducted a series of randomised controlled trials, which were carried out using Tencent Questionnaire.
Data analysis	We used Stata 18 for data cleaning, Python 3.11.7 for data analysis, NetLogo 6.4.0 for simulation and Gephi 0.10.1 for visualisation. The code used for data processing and analysis is available from the corresponding authors upon request and subject to the necessary data access approvals.

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The data supporting the main findings of this study are available from the corresponding authors upon request, subject to compliance with the laws of the People's Republic of China and approval from the Office of Research at Renmin University of China. The data are not publicly available due to their sensitive nature and the potential for identification, which could compromise research participant privacy.

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Reporting on sex and gender

Gender information was collected in the CEPS through self-reporting. When a respondent provided different answers across waves, we used the most recent response as the reference. The distribution of gender in the analytical sample was as follows: males 48.86% and females 51.14%. The analyses were performed on the full sample, with gender included as a covariate. We did not conduct separate analyses based on gender because gender differentiation was not the primary focus of this study.

Reporting on race, ethnicity, or other socially relevant groupings

In the main text, the socially constructed variables include dichotomous categories for highest educational level (below college vs college and above), family background (low vs high parental socioeconomic status) and the Big Five personality traits (lower 50% vs upper 50% in each dimension). The CEPS tracked respondents' educational trajectories, starting from middle school; the highest educational level was derived from respondents' self-reports across the five survey waves and then recoded into below college and college and above. Family background was measured using a principal component score derived from three variables reported by respondents in the baseline survey: parents' highest occupational socioeconomic status, parents' highest educational attainment, and household economic status. The continuous variable was then recoded into a dichotomous variable using the median as the cutoff point. The Big Five personality traits were derived from CEPS 2017, which collated the data using the Big Five Personality Scale. Respondents completed self-assessments, and scores for each of the five personality dimensions were calculated accordingly. For this study, the continuous variables were recoded into dichotomous variables using the median of each dimension as the cutoff point.

In the Supplementary Information, we compared the distributions of several sociodemographic variables between the overall sample and the subsample, including gender, ethnic group, hukou type, father's educational level, father's occupation, and area of residence (see Supplementary Table 7 for details). All the information was collected through self-reports.

Population characteristics

The CEPS baseline survey comprises a nationally representative sample of the 2013 middle school entry cohort. At the time of the survey, all respondents were in Grade 7, with the majority aged 12–13 years ($N = 10,279$; mean age = 12.58 [SD = 0.73]). The specific age distribution was as follows: 11 years old accounted for 2.05%, 12 years old for 48.88%, 13 years old for 40.10%, 14 years old for 7.38%, and 15 years old and above for 1.59%. Social media data were collected from May 2018, when most respondents were aged 17–18 years. Among the 8,636 respondents who granted us permission for social media data collection, the mean age was 17.57 (SD = 0.73). The specific age distribution was as follows: 16 years old accounted for 1.95%, 17 years old for 49.35%, 18 years old for 39.96%, 19 years old for 7.22%, and 20 years old and above for 1.52%. Among the 2,703 respondents who provided informed consent for the research team to link their WeChat activities with their offline survey data, the mean age was 17.59 (SD = 0.73). The specific age distribution for this group was as follows: 16 years old accounted for 1.61%, 17 years old for 49.01%, 18 years old for 40.21%, 19 years old for 7.39%, and 20 years old and above for 1.78%.

Recruitment

The nationwide survey CEPS began in 2013 and employed a probability-proportionate-to-size (PPS) sampling method. The smallest sampling unit was the class, and all students in the sampled classes were included in the survey. Ultimately, the survey included 10,279 Grade 7 students whose guardians provided informed consent for them to complete the student questionnaires. To obtain this consent, we worked with local educational institutions and schools to distribute an invitation letter to each selected student and their guardians. The letter explained the purpose of the survey, the sampling process, the organisation conducting the study, and the methods of ensuring data confidentiality, inviting both students and their guardians to participate. If guardians consented, they and the students would complete the guardian and student questionnaires, respectively. If they did not consent, neither the student nor the guardian was required to complete the questionnaires. In line with standard practices for general social surveys in China in 2013, written signatures were not required for non-medical research. The entire process adhered to the requirements of the Ethics Committee of the National Survey Research Center at Renmin University of China.

In 2018, with the approval of the Ethics Committee, we invited participants to grant the research team permission to access their online posts and interactions with their middle school classmates on WeChat for further research. The invitation message included the following statement, 'If you agree to participate, please provide your WeChat ID, which we will consider as your informed consent. Should you have any concerns, you may withdraw at any time by revoking the research team's access to the aforementioned permissions within the WeChat application'. A total of 8,636 respondents granted us permission. At the time of invitation, all survey participants were aged 16 or above. Under China's current legal framework, the collection, storage, or analysis of personal information from minors aged 14 or above requires only the minor's own consent and does not require consent from their parents or legal guardians (see Article 31 of the Personal Information

Protection Law of the People's Republic of China).

From these 8,636 respondents, we randomly selected half ($N = 4,318$) and requested permission to link their online activities on WeChat with their offline survey data. Participants provided consent by clicking 'Agree to participate' on a consent form approved by the Ethics Committee. This form outlined the study's purpose, potential risks, and measures for protecting personal information (e.g., the data linkage would be managed by designated personnel, all the researchers would sign confidentiality agreements, all the information would be stored on encrypted servers, and the data would be used solely for scientific research).

Of the 4,318 respondents to whom we sent the request to link their WeChat activities with their offline survey data, a total of 2,703 respondents provided informed consent. After applying listwise deletion to cases with missing values on key variables, 2,206 respondents were included in the final analytical sample. We compared key demographic variables between the analytical sample and the overall sample, and most did not show significant differences. To address potential self-selection bias, we implemented a weighting procedure to ensure that the subsample had the same covariate distributions as the full sample. The weighted results were similar to the unweighted ones (see Supplementary Table 15 and Supplementary Figs. 19–22 for details).

In terms of the randomised controlled trials, ethical approval was secured from the Science and Technology Ethics Committee at Tsinghua University on 6 June 2025 (Project No: THU-04-2025-1007). The participants were informed of the purpose of the research, how their data would be used, and the data protection measures. Informed consent was obtained from all the participants. All the survey participants were aged 17–21 at the time of invitation, and their individual consent was sufficient for participation in this study, in accordance with the current legal framework in China. We only collected participants' age range and gender: the former was used to exclude respondents who were not within the 17–21 age group, and the latter was asked for quota purposes. No other personal information was requested. The study was conducted in accordance with relevant guidelines of the Declaration of Helsinki.

The experiments were performed from 12–26 June 2025. We recruited eight groups of participants, and the sample size for each group was set to 100, with the gender ratio maintained at 1:1 for all the experiments. We used the Tencent Questionnaire platform to recruit the participants from among WeChat users, and each respondent was only allowed to participate in one experiment. We included two attention check questions in the questionnaire to filter out inattentive participants. If a participant did not pass these questions, they were excluded, and a new participant was recruited; this process was repeated until the target sample size was achieved. Eventually, a total of 800 individuals participated in the experiments: 400 males and 400 females. The participants were all 17–21 years of age and from 34 provinces in Mainland China.

Ethics oversight

Ethical approval was obtained from the Ethics Committee of the National Survey Research Center at Renmin University of China (Reference No. RN2012042201, RN2018041101) and from the Science and Technology Ethics Committee at Tsinghua University (Project No: THU-04-2025-1007).

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Study description

This is a quantitative study based on an online-and-offline-integrated dataset of a Generation Z cohort in China. We constructed an online network of 8,636 respondents using 1,048,999 online posts and 1,030,710 inner-circle interactions collected from May 2018 to April 2021. Additionally, we linked the online posts and interactions of a subsample of 2,703 respondents to their offline longitudinal survey data to examine the determinants of attracted attention on social media. Furthermore, we conducted a series of randomised controlled trials, including both between-subjects and within-subjects experimental designs with 800 participants.

Research sample

The CEPS research sample consisted of a Generation Z cohort born in 2000–2001, who were in Grade 7 when the baseline survey was conducted in 2013 ($N = 10,279$, mean age = 12.58 [SD = 0.73], male = 52.89%, female = 47.11%). The survey employed a probability-proportionate-to-size (PPS) sampling method, ensuring a representative sample. In 2018, 8,636 respondents granted permission for the survey team to access their online posts and interactions with their middle school classmates on WeChat. Of these 8,636 respondents, we randomly selected half ($N = 4,318$) and requested permission to link their online activities on WeChat with their offline survey data, and 2,703 provided informed consent. After applying listwise deletion to cases with missing values on key variables, the final analytical sample consisted of 2,206 respondents. A weighting procedure was implemented to ensure that the analytical sample had the same covariate distributions as the full sample. The experimental designs included 800 participants. We recruited eight groups of participants, and the sample size for each group was set to 100, with the gender ratio maintained at 1:1 for all the experiments.

Sampling strategy

The CEPS employs a multi-stage PPS sampling method comprising four stages. First stage: 28 counties were randomly drawn from all county-level administrative units nationwide. Second stage: Four middle schools were randomly drawn from within the geographic boundaries of each sampled county. Third stage: Two Grade 7 classes were randomly drawn from each sampled school. Fourth stage:

	The final CEPS sample consists of all students in the selected classes, along with their parents, homeroom teachers, subject teachers (Chinese, Mathematics, and English) and school administrators.
Data collection	The CEPS data were collected using a self-administered paper-and-pencil questionnaire for Wave 1 to Wave 3, and LimeSurvey for Wave 4 and Wave 5. The WeChat data were obtained through daily manual backups. Only the participants and interviewers were present during the data collection, and the interviewers were blinded to the study hypothesis during this process. The experimental data were collected using Tencent Questionnaire, and the participants were blinded to the study hypothesis during this process.
Timing	CEPS Wave 1: October 2013 – June 2014 CEPS Wave 2: October 2014 – June 2015 CEPS Wave 3: April 2015 – July 2016 CEPS Wave 4: October 2017 – February 2018 CEPS Wave 5: September 2019 – April 2020 Social Media Data Collection: May 2018 – April 2021 Experimental Data Collection: 12–26 June 2025
Data exclusions	We excluded respondents with missing values on at least one variable from the 2,703 respondents who provided informed consent to link their social media records with their offline survey data. After applying listwise deletion to cases with missing values on key variables, 2,206 respondents were included in the final analytical sample. Experimental data: We included two attention check questions in the questionnaire to filter out inattentive participants. If a participant did not pass these questions, they were excluded, and a new participant was recruited; this process was repeated until the target sample size was achieved.
Non-participation	CEPS Baseline Data (Wave 1): The smallest sampling unit was the class, and all students in the sampled classes were enrolled in the survey, except for several students who were absent. The response rate was 99.16%. CEPS Follow-Up Data: Over the following four waves (Waves 2 to 5), the average attrition rate was 6.47%. Social Media Data: In total, 8,636 out of 10,279 (84.02%) respondents granted the survey team permission to access their online posts and interactions with their middle school classmates on WeChat. Additionally, of the 4,318 respondents to whom we sent the request to link their online WeChat activities with their survey data, 2,703 respondents (62.60%) provided informed consent.
Randomization	For randomised controlled trials, the participants were randomly assigned to either the control group/condition or the experimental group/condition, each of which comprised 100 participants with a balanced gender ratio.

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