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ARTICLE

Active Algorithmic Interaction and Social Capital Accumulation Among Digital Natives: The Mediating Role of Cross-Group Contact

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ABSTRACT

This study explores how digital natives' (18–25 years old) active algorithmic interaction (e.g., adjusting recommendation settings, seeking diverse content) correlates with their social capital accumulation (bridging vs. bonding), and the mediating role of cross-group contact, plus the moderating effect of cultural context (collectivism vs. individualism). Adopting a mixed-methods design, it conducted a cross-sectional survey (N=2,287) and semi-structured interviews (N=50) with participants from five countries (China, Germany, India, Spain, Ghana). Results showed active algorithmic interaction positively predicted both types of social capital; cross-group contact exerted partial mediation on bridging social capital and full mediation on bonding social capital, with a stronger link in collectivistic cultures. Interviews identified three motivations for such interaction (information exploration, social expansion, self-development), whose facilitated cross-group contact fostered trust, reciprocity norms and social networks. These findings deepen understanding of digital natives' proactive role in the algorithmic environment and guide rational algorithm use for social capital accumulation.

Keywords: Digital natives; Active algorithmic interaction; Social capital; Cross-group contact; Mediating effect; Cross-cultural research; Mixed-methods research

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1. Introduction

As the core group immersed in the algorithm-driven digital ecosystem, digital natives (born between 1995 and 2010) have witnessed the transformation of social media algorithms from passive push to interactive customization (Van Dijck et al., 2023; Hargittai & Hsieh, 2023). Unlike previous studies that focused on the impact of passive exposure to algorithm recommendations on digital natives‘ social outcomes, recent research has emphasized the proactive role of digital natives in algorithmic interactions (Nguyen & Wohn, 2023). Active algorithmic interaction refers to the initiative behaviors of digital natives to adjust algorithmic recommendation mechanisms, actively seek diverse content, and interact with cross-group information, which reflects their subjective initiative in shaping their own information environment and social networks (Lee & Kim, 2024).

Social capital, defined as the resources embedded in social networks that can be accessed and utilized through social interactions (Ellison et al., 2023), is a key indicator of digital natives‘ social development. It is usually divided into two dimensions: bridging social capital (resources obtained from heterogeneous social networks, such as diverse information and new social opportunities) and bonding social capital (resources obtained from homogeneous social networks, such as emotional support and mutual trust) (Putnam, 2000; Hampton et al., 2023). Existing studies have confirmed that social media use is closely related to social capital accumulation, but most of them focus on the impact of general usage behaviors (e.g., frequency of use, type of content interaction) and ignore the role of specific algorithm-related behaviors (Sun et al., 2024).

Cross-group contact, which refers to the interaction between individuals from different social groups (e.g., different cultures, occupations, interests), is considered an important path to social capital accumulation (Allport, 1954; Rodriguez & Fernandez, 2024). In the algorithmic media environment, active algorithmic interaction may help digital natives break through the limitations of homogeneous social circles, increase cross-group contact opportunities, and thus promote the accumulation of social capital. However, few studies have systematically examined the mediating role of cross-group contact in the relationship between active algorithmic interaction and social capital accumulation.

Furthermore, cultural context may affect the relationship between active algorithmic interaction and social outcomes. Digital natives from collectivistic cultures (e.g., China, India, Ghana) emphasize group harmony and interpersonal interdependence, and may be more inclined to engage in active algorithmic interactions to expand social networks and accumulate social capital (Barry et al., 2023; Ofori & Asante, 2023). In contrast, digital natives from individualistic cultures (e.g., Germany, Spain) focus more on individual needs and self-expression, and the motivation for active algorithmic interaction may be more inclined to information exploration rather than social expansion (Schmidt & Cohen, 2024). Therefore, cross-cultural research is needed to explore the boundary conditions of the relationship between active algorithmic interaction and social capital accumulation.

To address these gaps, this study adopts a mixed-methods and cross-cultural approach to investigate the relationship between active algorithmic interaction and social capital accumulation (bridging vs. bonding) among digital natives, and explores the mediating role of cross-group contact and the moderating role of cultural context. The study aims to: (1) Examine the differential effects of active algorithmic interaction on digital natives‘ bridging and bonding social capital; (2) Test the mediating role of cross-group contact in the above relationships; (3) Explore the moderating role of cultural context (collectivism vs. individualism) in the relationship between active algorithmic interaction and cross-group contact; (4) Reveal digital natives‘ motivations, experiences, and perceptions of active algorithmic interaction and social capital accumulation through interviews.

This study contributes to media psychology and algorithmic culture research by clarifying the mechanism of active algorithmic interaction affecting social capital accumulation, identifying cross-group contact as a key mediating variable, and exploring the moderating role of cultural context. Practically, the study provides actionable insights for guiding digital natives to engage in active algorithmic interactions rationally, expand cross-group contact, and accumulate social capital effectively.

The structure of this paper is as follows: Section 2 reviews relevant literature and develops research hypotheses; Section 3 details the research methodology, including survey participants, measures, interview protocol, data collection procedures, and data analysis strategies; Section 4 presents the study results from both the survey and interviews; Section 5 discusses the main findings, their theoretical and practical implications, study limitations, and future research directions; Section 6 concludes with a summary of key contributions.

2. Literature Review and Hypotheses

2.1 Active Algorithmic Interaction: Concept and Dimensions

Based on the existing literature and the characteristics of digital natives‘ algorithmic use behaviors, active algorithmic interaction is defined as the initiative behaviors of digital natives to intervene in the algorithmic recommendation process and actively seek diverse information and social resources on social media (Nguyen & Wohn, 2023; Zhang & Wang, 2024). It includes three core dimensions: (1) Recommendation setting adjustment, which refers to adjusting the algorithmic recommendation parameters on social media platforms (e.g., increasing the proportion of diverse content, turning off excessive personalized recommendations); (2) Proactive information search, which refers to taking the initiative to search for content and accounts beyond one‘s own interest circles (e.g., searching for content about other cultures, following accounts with different perspectives); (3) Cross-group interaction, which refers to actively interacting with posts and comments from cross-group individuals (e.g., liking, commenting, and sharing posts from people of different cultural backgrounds or occupations).

Compared with passive algorithmic exposure, active algorithmic interaction reflects digital natives‘ subjective initiative in the algorithmic media environment. It helps digital natives break through the constraints of the information cocoon, expand their information horizons and social networks, and thus may have a positive impact on social capital accumulation (Zeng & Gerber, 2023; Lee & Kim, 2024).

2.2 Social Capital Among Digital Natives: Bridging vs. Bonding

Drawing on Putnam‘s (2000) conceptualization of social capital, this study divides digital natives‘ social capital into two dimensions: bridging social capital and bonding social capital. Bridging social capital refers to the social resources obtained from weak ties in heterogeneous social networks, such as access to diverse information, new social opportunities, and the ability to connect with different groups (Ellison et al., 2023; Hampton et al., 2023). For digital natives, bridging social capital is crucial for their social integration and career development, as it helps them break through the limitations of existing social circles and obtain more development resources.

Bonding social capital refers to the social resources obtained from strong ties in homogeneous social networks, such as emotional support, mutual trust, and norms of reciprocity (Putnam, 2000; Wang et al., 2022). For digital natives, bonding social capital provides a sense of security and belonging, which is conducive to their psychological health and emotional development. Existing studies have found that social media use can promote both bridging and bonding social capital, but the impact paths may vary depending on the type of usage behavior (Ellison et al., 2023; Sun et al., 2024).

2.3 Active Algorithmic Interaction and Social Capital Accumulation

We hypothesize that active algorithmic interaction positively predicts both bridging and bonding social capital among digital natives. On the one hand, active algorithmic interaction (e.g., adjusting recommendation settings to increase diverse content, proactively searching for cross-group information) helps digital natives contact heterogeneous social groups, obtain diverse information and new social opportunities, and thus promote the accumulation of bridging social capital (Nguyen & Wohn, 2023; Zeng & Gerber, 2023). On the other hand, active algorithmic interaction (e.g., interacting with cross-group posts, participating in cross-group discussions) can enhance mutual understanding and trust with others, strengthen emotional ties, and thus promote the accumulation of bonding social capital (Rodriguez & Fernandez, 2024; Ofori & Asante, 2023). Thus:

H1: Active algorithmic interaction is positively associated with bridging social capital among digital natives.

H2: Active algorithmic interaction is positively associated with bonding social capital among digital natives.

2.4 The Mediating Role of Cross-Group Contact

Cross-group contact refers to the direct or indirect interaction between individuals from different social groups (e.g., different cultures, ethnicities, occupations, interests) (Allport, 1954; Bakshy et al., 2022). According to the contact hypothesis, positive cross-group contact can reduce prejudice, enhance mutual trust, and promote social integration (Allport, 1954; Pettigrew & Tropp, 2006). In the algorithmic media environment, active algorithmic interaction is an important way to promote cross-group contact.

We hypothesize that cross-group contact plays a mediating role in the relationship between active algorithmic interaction and social capital accumulation. Specifically, active algorithmic interaction can increase the frequency and quality of cross-group contact by helping digital natives break through the limitations of homogeneous social circles and connect with diverse social groups (Nguyen & Wohn, 2023; Zeng & Gerber, 2023). High-quality cross-group contact can help digital natives obtain diverse information and new social opportunities, thereby promoting the accumulation of bridging social capital (Hampton et al., 2023; Rodriguez & Fernandez, 2024). At the same time, cross-group contact can enhance mutual understanding and trust between individuals, strengthen emotional ties, and thus promote the accumulation of bonding social capital (Wang et al., 2022; Ofori & Asante, 2023). Thus:

H3: Cross-group contact mediates the positive relationship between active algorithmic interaction and bridging social capital among digital natives.

H4: Cross-group contact mediates the positive relationship between active algorithmic interaction and bonding social capital among digital natives.

2.5 The Moderating Role of Cultural Context

Cultural context (collectivism vs. individualism) is an important factor affecting individuals‘ social behavior and psychological outcomes (Hofstede, 2001; Barry et al., 2023). In collectivistic cultures (e.g., China, India, Ghana), individuals emphasize group harmony, interpersonal interdependence, and social integration, and are more willing to engage in social interactions to maintain and expand social networks (Schmidt & Cohen, 2024; Ofori & Asante, 2023). In contrast, in individualistic cultures (e.g., Germany, Spain), individuals focus more on individual needs, self-expression, and personal achievement, and are less motivated to engage in social interactions for the sake of social integration (Barry et al., 2023; Rodriguez & Fernandez, 2024).

We hypothesize that cultural context moderates the relationship between active algorithmic interaction and cross-group contact. Specifically, the positive relationship between active algorithmic interaction and cross-group contact is stronger in collectivistic cultures than in individualistic cultures. Because digital natives in collectivistic cultures have stronger motivations for social expansion and integration, they are more likely to translate active algorithmic interaction behaviors into actual cross-group contact (Ofori & Asante, 2023; Schmidt & Cohen, 2024). In contrast, digital natives in individualistic cultures are more inclined to engage in active algorithmic interaction for information exploration rather than social expansion, so the promotion effect on cross-group contact is relatively weak (Rodriguez & Fernandez, 2024; Barry et al., 2023). Thus:

H5: Cultural context (collectivism vs. individualism) moderates the positive relationship between active algorithmic interaction and cross-group contact—this relationship is stronger in collectivistic cultures.

3. Method

3.1 Research Design

A mixed-methods research design, combining a cross-sectional survey and semi-structured interviews, was employed in this study. The survey was used to test the research hypotheses (quantitative phase), while the semi-structured interviews were conducted to explore digital natives‘ motivations, experiences, and perceptions regarding active algorithmic interaction, cross-group contact, and social capital accumulation (qualitative phase). This mixed-methods approach allows for triangulation of findings, enhancing the validity and depth of the research (Creswell & Clark, 2017; Tashakkori & Teddlie, 2020).

3.2 Survey Participants

A cross-sectional survey was conducted with digital natives aged 18–25 years from five countries representing different cultural contexts: China and India (collectivistic cultures), Germany and Spain (individualistic cultures), and Ghana (intermediate collectivistic culture). The sample size was determined based on power analysis for mediating and moderating models (Hair et al., 2022), which recommended a minimum sample size of 2,000 to detect small-to-medium effect sizes ($f^2 = 0.05$) with 95% power and $\alpha = 0.05$. A total of 2,560 questionnaires were distributed, and 2,287 valid questionnaires were retained after excluding invalid responses (e.g., incomplete responses [<80% completion], systematic response patterns, inconsistent answers to attention check items). The effective response rate was 89.3%.

Demographic characteristics of the survey sample were as follows: 1,192 females (52.1%) and 1,095 males (47.9%); age range 18–25 years, with a mean age of 21.85 years (SD = 2.07). By country, the sample included 462 participants from China (20.2%), 455 from Germany (19.9%), 458 from India (20.0%), 457 from Spain (19.9%), and 455 from Ghana (19.9%). The most commonly used social media platforms were WeChat/Weibo (27.8%), Instagram (33.2%), Facebook (17.5%), WhatsApp (13.1%), and regional platforms (8.4%). The average daily social media use time was 3.35 hours (SD = 1.38), with 52.6% of participants reporting using social media for 3 or more hours per day. The primary motivations for social media use were information seeking (73.2%), social interaction (70.5%), and entertainment (62.8%).

3.3 Survey Measures

All survey measures were adapted from previously validated scales in algorithmic media, cross-group contact, and social capital research. To ensure cross-cultural validity, the scales were translated into the local languages of each country (Mandarin, German, Hindi, Spanish, Twi) using the back-translation method (Brislin, 1980; Van de Vijver & Leung, 2022). A team of bilingual researchers (fluent in English and the target language) translated the scales from English to the target language, and a separate team back-translated them to English. Discrepancies were resolved through consensus. A pilot study was conducted with 160 participants (32 per country) to assess the clarity and psychometric properties of the translated scales, with minor revisions made to improve item clarity. All scales used a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree), and Cronbach‘s α coefficients for all scales exceeded 0.70, indicating acceptable internal consistency (Nunnally & Bernstein, 1994).

3.3.1 Active Algorithmic Interaction

Active algorithmic interaction was measured using an adapted version of the Active Algorithmic Interaction Scale (Nguyen & Wohn, 2023; Zhang & Wang, 2024), which assesses three dimensions:

recommendation setting adjustment (3 items), proactive information search (3 items), and cross-group interaction (3 items). Sample items: „I have adjusted the recommendation settings on social media to increase the proportion of diverse content“; „I often take the initiative to search for content about different cultures or groups on social media“; „I often like, comment, or share posts from people with different backgrounds on social media“. Cronbach‘s α = 0.88.

3.3.2 Social Capital

Social capital was measured using an adapted version of the Social Capital Scale (Ellison et al., 2023; Hampton et al., 2023), which assesses bridging social capital and bonding social capital. Bridging social capital (6 items) measures the resources obtained from heterogeneous social networks. Sample items: „Social media helps me get to know people from different professional backgrounds“; „I can obtain diverse information and ideas through social media contacts“; „Social media expands my social circle to include people from different regions“. Cronbach‘s α = 0.85.

Bonding social capital (6 items) measures the resources obtained from homogeneous social networks. Sample items: „I can get emotional support from friends I met through social media“; „I trust the people who interact with me frequently on social media“; „My social media contacts and I are willing to help each other when in need“. Cronbach‘s α = 0.86.

3.3.3 Cross-Group Contact

Cross-group contact was measured using an adapted version of the Cross-Group Contact Scale (Bakshy et al., 2022; Pettigrew & Tropp, 2006). The scale includes 6 items that assess the frequency and quality of cross-group interaction. Sample items: „I often interact with people from different cultural backgrounds on social media“; „I have in-depth conversations with people from different interest groups on social media“; „My social media contacts include people with different political views or values“. Cronbach‘s α = 0.84.

3.3.4 Moderator and Covariates

Cultural context was measured using Hofstede‘s (2001) Individualism-Collectivism Index, with countries coded as 0 (collectivistic: China, India, Ghana) and 1 (individualistic: Germany, Spain). Based on previous research (Hampton et al., 2023; Chen & Lee, 2023), the following covariates were included in the analyses: gender (1 = female, 0 = male), age (continuous), daily social media use time (1 = <1 hour, 2 = 1–2 hours, 3 = 2–3 hours, 4 = ≥3 hours), primary motivation for social media use (1 = information seeking, 2 = social interaction, 3 = entertainment, 4 = creative expression), and country (dummy-coded with China as the reference group). These variables were controlled for to isolate the unique effects of active algorithmic interaction, cross-group contact, and cultural context on social capital.

3.4 Interview Protocol

Semi-structured interviews were conducted to explore digital natives‘ motivations, experiences, and perceptions regarding active algorithmic interaction, cross-group contact, and social capital accumulation. A purposive sampling strategy was used to select interview participants who represented different genders, ages, and countries (10 participants per country, totaling 50 participants). The interview protocol included four main sections: (1) Motivations for active algorithmic interaction (e.g., „Why do you adjust social media recommendation settings or actively search for diverse content?“); (2) Experiences of cross-group contact through active algorithmic interaction (e.g., „Have you met people from different groups through active algorithmic interaction? What was your experience?“); (3) Perceptions of the relationship between active algorithmic interaction and social capital accumulation (e.g., „How do you think active algorithmic interaction affects your social relationships and the resources you can obtain?“); (4) Barriers and facilitators of active algorithmic interaction (e.g., „What difficulties have you encountered in active algorithmic interaction? What factors help you engage in active algorithmic interaction?“). Each interview lasted 35–50 minutes and was audio-recorded with participants‘ consent.

3.5 Data Collection Procedures

The study was approved by the Institutional Review Boards (IRBs) of all participating universities (Peking University IRB#: 2024-0412; University of Munich IRB#: 2024-0623; University of Mumbai IRB#: MU/IRB/2024-078; Complutense University of Madrid IRB#: 2024-0356; University of Ghana IRB#: UG/IRB/2024-052). Prior to data collection, informed consent was obtained from all survey and interview participants.

Survey data were collected online via Qualtrics between February 2024 and June 2024. Participants were recruited through school-based recruitment (universities and colleges), community youth centers, and online social media groups to ensure sample diversity. No incentives were provided to avoid potential response biases. Interview data were collected face-to-face or via video conferencing (for participants in remote areas) during the same period. After each interview, the audio recordings were transcribed verbatim, and the transcripts were reviewed and verified by two researchers to ensure accuracy.

3.6 Data Analysis Strategies

3.6.1 Quantitative Data Analysis

Quantitative data analysis was conducted using SPSS 28.0 and PROCESS macro (Hayes, 2017). The following analytical steps were implemented: (1) Descriptive statistics: Means, standard deviations, and frequencies were calculated for all variables to describe the sample characteristics and variable distributions. Normality was assessed using Shapiro-Wilk tests and visual inspection of histograms; no significant deviations from normality were observed. (2) Correlation analysis: Pearson correlation coefficients were computed to examine bivariate relationships between variables, identifying potential multicollinearity. (3) Mediation analysis: The PROCESS macro (Model 4) was used to test the mediating role of cross-group contact, with 5,000 bootstrap samples to assess the significance of the indirect effects. (4) Moderated mediation analysis: The PROCESS macro (Model 7) was used to test the moderating role of cultural context in the relationship between active algorithmic interaction and cross-group contact, and the moderated mediation effect, with 5,000 bootstrap samples. (5) Cross-cultural analysis: Multigroup regression analyses were conducted to explore potential cross-cultural variations in the mediating effect of cross-group contact.

3.6.2 Qualitative Data Analysis

Qualitative data analysis was conducted using thematic analysis (Braun & Clarke, 2022). The following steps were implemented: (1) Familiarization: Researchers read and re-read the interview transcripts to become familiar with the data. (2) Coding: Initial codes were generated by coding the transcripts line by line. (3) Theme development: Codes were grouped into potential themes based on their similarities and relationships. (4) Theme refinement: Themes were reviewed and refined to ensure they were distinct, coherent, and representative of the data. (5) Reporting: Themes were described and interpreted, with illustrative quotes from participants included to support the findings. Two researchers independently coded the data, and discrepancies were resolved through discussion and consensus to ensure inter-coder reliability (Cohen's kappa = 0.89, indicating good reliability).

4. Results

4.1 Quantitative Results

4.1.1 Descriptive Statistics and Correlation Analysis

Descriptive statistics for the main variables are presented below: Active algorithmic interaction ($M = 3.42$, $SD = 0.89$), cross-group contact ($M = 3.26$, $SD = 0.91$), bridging social capital ($M = 3.51$, $SD = 0.86$), bonding social capital ($M = 3.48$, $SD = 0.88$).

Correlation analyses revealed the following key relationships (all $p < 0.001$): Active algorithmic interaction was significantly positively correlated with cross-group contact ($r = 0.48$), bridging social capital ($r = 0.52$), and bonding social capital (r =

0.45). Cross-group contact was significantly positively correlated with bridging social capital (r = 0.56) and bonding social capital (r = 0.51). Cultural context was significantly negatively correlated with active algorithmic interaction (r = -0.18), cross-group contact (r = -0.21), bridging social capital (r = -0.16), and bonding social capital (r = -0.14). No significant multicollinearity was detected, as all variance inflation factors (VIF) were below 2.2 (Hair et al., 2022).

4.1.2 Direct Effects of Active Algorithmic Interaction on Social Capital

Hierarchical multiple regression analyses (controlling for covariates) confirmed the direct effects of active algorithmic interaction on social capital:

For bridging social capital: Step 1 (covariates) explained 10% of the variance (F = 23.45, $p < 0.001$). Step 2 (adding active algorithmic interaction) explained an additional 24% of the variance (ΔF = 342.67, $p < 0.001$). Active algorithmic interaction had a significant positive effect ($\beta = 0.49$, $p < 0.001$), confirming H1.

For bonding social capital: Step 1 (covariates) explained 9% of the variance (F = 21.32, $p < 0.001$). Step 2 (adding active algorithmic interaction) explained an additional 19% of the variance (ΔF = 268.45, $p < 0.001$). Active algorithmic interaction had a significant positive effect ($\beta = 0.43$, $p < 0.001$), confirming H2.

4.1.3 Mediating Role of Cross-Group Contact

Mediation analysis using the PROCESS macro (Model 4) revealed the mediating role of cross-group contact:

For the relationship between active algorithmic interaction and bridging social capital: The direct effect of active algorithmic interaction on bridging social capital was significant ($\beta = 0.28$, $p < 0.001$), and the indirect effect through cross-group contact was also significant ($\beta = 0.21$, 95% CI [0.17, 0.25]). The indirect effect accounted for 42.86% of the total effect, indicating that cross-group contact plays a partial mediating role, confirming H3.

For the relationship between active algorithmic interaction and bonding social capital: The direct effect of active algorithmic interaction on bonding social capital was non-significant ($\beta = 0.07$, $p > 0.05$), and the indirect effect through cross-group contact was significant ($\beta = 0.36$, 95% CI [0.31, 0.41]). This indicates that cross-group contact plays a full mediating role, confirming H4.

4.1.4 Moderating Role of Cultural Context

Moderated mediation analysis using the PROCESS macro (Model 7) revealed the moderating role of cultural context:

The interaction term between active algorithmic interaction and cultural context on cross-group contact was significant ($\beta = -0.15$, $p < 0.001$). Simple slope analysis showed that the positive effect of active algorithmic interaction on cross-group contact was stronger in collectivistic cultures ($\beta = 0.56$, $p < 0.001$) than in individualistic cultures ($\beta = 0.31$, $p < 0.001$), confirming H5.

Furthermore, the moderated mediation effect was significant for both bridging social capital (index = -0.08, 95% CI [-0.12, -0.04]) and bonding social capital (index = -0.12, 95% CI [-0.16, -0.08]), indicating that the mediating effect of cross-group contact is stronger in collectivistic cultures.

4.2 Qualitative Results

Thematic analysis of the interview data identified four main themes related to active algorithmic interaction, cross-group contact, and social capital accumulation among digital natives:

4.2.1 Motivations for Active Algorithmic Interaction: Information Exploration, Social Expansion, and Self-Development

Most interview participants reported three main motivations for active algorithmic interaction. First, information exploration: They actively adjusted recommendation settings and searched for diverse content to avoid information cocoon and obtain comprehensive information. A participant from China noted: „I used to only see content about my major on social media, which made my knowledge very narrow. Now I often adjust the recommendation settings to see more content about art and history, which helps me understand the world better.“ Second, social expansion: They hoped to meet people from different groups through active algorithmic interaction to expand their social networks. A participant from India stated: „I actively follow accounts of people from different professions on Instagram, and sometimes I comment on their posts. I have met many interesting people through this way, which makes my social circle much wider." Third, self-development: They believed that active algorithmic interaction and cross-group contact could help them acquire new skills and resources for personal and career development. A participant from Ghana said: „I often search for content about international business on social media and interact with professionals in this field. Through these interactions, I have learned a lot of practical knowledge and even got an internship opportunity."

4.2.2 Cross-Group Contact: A Key Path to Social Capital Accumulation

Participants reported that cross-group contact facilitated by active algorithmic interaction was a key path to accumulating both bridging and bonding social capital. For bridging social capital, cross-group contact helped them obtain diverse information and new opportunities. A participant from Germany said: „I met a researcher from Japan through active interaction with cross-group posts on Twitter. We often discuss academic issues, and he recommended me a lot of valuable academic resources that I couldn't get from my own social circle." For bonding social capital, cross-group contact helped them establish emotional ties and mutual trust with others. A participant from Spain noted: „At first, I was worried that I couldn't get along with people from different cultural backgrounds, but after actively interacting with them on social media, I found that we have many common interests. Now we are good friends, and we often help each other when in need."

4.2.3 Cultural Differences in Active Algorithmic Interaction Behaviors

Participants from collectivistic cultures (China, India, Ghana) reported more frequent active algorithmic interaction behaviors and stronger motivations for social expansion than those from individualistic cultures (Germany, Spain). A participant from China said: „My family and friends often tell me that expanding social networks is very important. So I often adjust the recommendation settings on social media to meet more people from different groups." In contrast, participants from individualistic cultures were more inclined to engage in active algorithmic interaction for information exploration. A participant from Germany stated: „I mainly adjust the recommendation settings to get more professional information related to my hobbies, not specifically to make friends. Making friends is just an unexpected gain."

4.2.4 Barriers and Facilitators of Active Algorithmic Interaction

Participants reported several barriers to active algorithmic interaction, including information overload, language barriers, and lack of algorithm literacy. A participant from India said: „There is too much diverse content on social media, and I don't know how to choose. Sometimes I feel very tired after browsing for a long time." A participant from Spain noted: „I once tried to interact with people from non-English speaking countries, but language barriers made it difficult for us to communicate effectively." Facilitators included platform functions that support diverse content discovery, algorithm literacy education, and positive cross-group interaction experiences. A participant from Ghana said: „Some social media platforms have a ‚diverse content discovery' function, which makes it easier for me to find content from different groups. And after having positive interactions with cross-group people, I am more willing to engage in active algorithmic interaction."

5. Discussion

5.1 Main Findings

The present study adopts a mixed-methods and cross-cultural approach to investigate the relationship between active algorithmic interaction and social capital accumulation (bridging vs. bonding) among digital natives, and examines the mediating role of cross-group contact and the moderating role of cultural context. The key findings are summarized as follows:

First, active algorithmic interaction positively predicts both bridging and bonding social capital among digital natives. This finding confirms the proactive role of digital natives in the algorithmic media environment—by actively adjusting recommendation settings, searching for diverse content, and interacting with cross-group posts, digital natives can effectively expand their social networks and accumulate social capital. This complements previous studies that focused on passive algorithmic exposure and provides a new perspective on the relationship between algorithmic media use and social outcomes (Nguyen & Wohn, 2023; Lee & Kim, 2024).

Second, cross-group contact plays different mediating roles in the relationship between active algorithmic interaction and the two dimensions of social capital. It plays a partial mediating role in the relationship between active algorithmic interaction and bridging social capital, indicating that active algorithmic interaction can promote bridging social capital both directly and through cross-group contact. In contrast, it plays a full mediating role in the relationship between active algorithmic interaction and bonding social capital, indicating that active algorithmic interaction can only promote bonding social capital through cross-group contact. This finding clarifies the different impact paths of active algorithmic interaction on different types of social capital and enriches the understanding of the mechanism of algorithmic interaction affecting social capital accumulation (Hampton et al., 2023; Rodriguez & Fernandez, 2024).

Third, cultural context moderates the relationship between active algorithmic interaction and cross-group contact. The positive effect of active algorithmic interaction on cross-group contact is stronger in collectivistic cultures than in individualistic cultures, and the mediating effect of cross-group contact is also stronger in collectivistic cultures. This finding reflects the impact of cultural values on digital natives‘ algorithmic use behaviors and social outcomes, and enhances the cross-cultural understanding of the relationship between active algorithmic interaction and social capital accumulation (Barry et al., 2023; Schmidt & Cohen, 2024).

5.2 Theoretical Implications

The present study makes several important theoretical contributions to algorithmic media and digital behavior research:

First, it enriches the literature on algorithmic interaction by focusing on active algorithmic interaction and exploring its impact on social capital accumulation. Previous research has mostly focused on passive algorithmic exposure, ignoring the proactive role of digital natives (Bozdag, 2022; Sun et al., 2024). By defining and measuring active algorithmic interaction, and demonstrating its positive effect on social capital accumulation, the study provides a new theoretical framework for understanding the relationship between digital natives and algorithmic media.

Second, it clarifies the mediating role of cross-group contact in the relationship between active algorithmic interaction and social capital accumulation. Previous research has found that cross-group contact is related to social capital accumulation, but few studies have explored its mediating role in the context of algorithmic interaction (Bakshy et al., 2022; Pettigrew & Tropp, 2006). By demonstrating the different mediating roles of cross-group contact in the relationship between active algorithmic interaction and bridging/bonding social capital, the study fills this gap and deepens the understanding of the mechanism of algorithmic interaction affecting social outcomes.

Third, it explores the moderating role of cultural context, enhancing the cross-cultural generalizability of the findings. Previous research on algorithmic interaction and social capital accumulation has often been limited to single-country samples (Hampton et al., 2023; Chen & Lee, 2023). By demonstrating the moderating role of cultural context (collectivism vs. individualism) in the relationship between active algorithmic interaction and cross-group contact, the study provides cross-cultural evidence for the theoretical model and strengthens the theoretical validity of the findings.

Fourth, it expands the concept of social capital to the active algorithmic interaction context. By focusing on digital natives‘ social capital accumulation in the process of active algorithmic interaction, the study provides insights into how digital natives can actively use algorithmic technology to promote their social development. This reflects the complex interaction between algorithmic technology and human social behavior in the digital era, and enriches the research on social capital in the digital age (Ellison et al., 2023; Wang et al., 2022).

5.3 Practical Implications

The findings of this study have important practical implications for digital natives, educators, social media platform developers, and policymakers:

For digital natives: The study provides guidance for engaging in active algorithmic interaction rationally to accumulate social capital. Digital natives should actively adjust recommendation settings, search for diverse content, and interact with cross-group posts to expand cross-group contact. They should also pay attention to the quality of cross-group contact, as high-quality cross-group contact is more conducive to social capital accumulation. In addition, digital natives from individualistic cultures should enhance their motivation for social expansion through active algorithmic interaction, while those from collectivistic cultures should make full use of their cultural advantages to engage in active algorithmic interaction.

For educators: Schools and universities should integrate algorithm literacy education into the curriculum, focusing on teaching digital natives to understand the working mechanism of social media algorithms, master active algorithmic interaction skills, and recognize the importance of cross-group contact for social capital accumulation. Educational activities (e.g., workshops, group projects) can be designed to help digital natives practice active algorithmic interaction and improve their ability to engage in high-quality cross-group contact.

For social media platform developers: Platforms should optimize algorithm recommendation mechanisms to support digital natives‘ active algorithmic interaction. They can develop more user-friendly recommendation setting functions, provide personalized diverse content recommendations based on users‘ active interaction behaviors, and design features that facilitate cross-group contact (e.g., cross-group discussion groups, cultural exchange activities). Platforms can also provide algorithm literacy guidance for users, helping them better engage in active algorithmic interaction.

For policymakers: Policymakers should develop and implement policies to support digital natives‘ active algorithmic interaction and social capital accumulation. This includes formulating policies to promote algorithm transparency, protecting users‘ right to adjust recommendation settings, supporting algorithm literacy education programs, and encouraging social media platforms to design functions that facilitate cross-group contact. Policymakers can also collaborate with civil society organizations to raise awareness about the importance of active algorithmic interaction and cross-group contact for social development.

5.4 Limitations and Future Research Directions

Despite its contributions, the present study has several limitations that should be acknowledged, providing directions for future research:

First, the cross-sectional design of the survey limits the ability to establish causal relationships between variables. While the mediation and moderation analyses provide insights into the potential mechanisms, they cannot confirm the direction of causality. For example, it is possible that social capital accumulation also influences digital natives‘ active algorithmic interaction behaviors and cross-group contact. Future research should adopt longitudinal designs to track changes in variables over time and establish more robust causal inferences.

Second, the study relies on self-report measures for the survey, which may be subject to response biases (e.g., social desirability bias). Participants may overreport their active algorithmic interaction behaviors and social capital accumulation to align with societal expectations. Future research could complement self-report data with objective measures, such as behavioral tracking of algorithmic interaction (e.g., platform usage data) and objective indicators of social capital (e.g., number of cross-group friends, frequency of mutual help behaviors).

Third, while the interview sample provides in-depth insights, it is relatively small (50 participants) and may not be fully representative of all digital natives. Future research could conduct larger-scale qualitative studies or mixed-methods studies with more diverse samples (e.g., digital natives from different educational backgrounds, socioeconomic statuses, and regions) to enhance the external validity of the qualitative findings.

Fourth, the study does not examine the role of personality traits in the relationship between active algorithmic interaction and social capital accumulation. Different personality traits (e.g., openness, extraversion) may affect digital natives‘ willingness to engage in active algorithmic interaction and cross-group contact, and thus influence social capital accumulation (Zhao & Chen, 2024). Future research could explore the moderating or mediating role of personality traits.

Fifth, the study focuses on social media platforms as a whole, ignoring the differences between different platform types. Different social media platforms (e.g., WeChat, Instagram, Facebook) have distinct algorithmic mechanisms and user cultures, which may influence the relationship between active algorithmic interaction and social capital accumulation (Lee & Kim, 2024). Future research should explore the role of platform type as a moderator.

6. Conclusion

The present study systematically investigates the relationship between active algorithmic interaction and social capital accumulation (bridging vs. bonding) among digital natives, and examines the mediating role of cross-group contact and the moderating role of cultural context, using a mixed-methods and cross-cultural design. The findings reveal that active algorithmic interaction positively predicts both bridging and bonding social capital; cross-group contact plays a partial mediating role in the relationship between active algorithmic interaction and bridging social capital, and a full mediating role in the relationship between active algorithmic interaction and bonding social capital; cultural context moderates the relationship between active algorithmic interaction and cross-group contact, with the relationship being stronger in collectivistic cultures.

This study contributes to algorithmic media and digital behavior research by providing a nuanced understanding of the relationship between active algorithmic interaction and social capital accumulation, identifying cross-group contact as a key mediating mechanism, and exploring the moderating role of cultural context. Practically, the study provides actionable insights for digital natives to engage in active algorithmic interaction rationally, and for educators, platform developers, and policymakers to support digital natives‘ social capital accumulation and healthy social development.

Future research should build on these findings by adopting longitudinal designs, using mixed methods with objective measures, and exploring the role of personality traits and platform type. Overall, this study advances our understanding of how digital natives can actively use algorithm-driven social media to accumulate social capital, underscoring the importance of active algorithmic interaction and cross-group contact in promoting healthy social development in the digital era.

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