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AI-Driven Digital Media Consumption: Generational Shifts, Algorithmic Trust, and Ethical Personalization – A Mixed-Methods Investigation

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Abstract
The fast adoption of artificial intelligence in online media has changed significantly the consumption pattern of the content by generations. This is a mixed-method study, which explores the relative differences in the use of digital media, trust in algorithmic suggestions, and ethical personalization among generational cohorts.They, instead, surveyed 4 generations (Gen Z, Millennials, Gen X and Baby Boomers) in the country (N=1,024) and later interviewed 48 (semi-structured interviews) (the length of the interviews was the same).Thematic analysis and Structural Equation Modeling revealed that the level of the algorithmic trust and ethical issues differed greatly across generations. Though younger generations turned out to be more engaged with customized content, there was a reduced trust in the algorithms due to the fear of privacy issues and manipulation. The paper recommends a system of ethical personalization which is both balanced in terms of autonomy, transparency and user involvement. Platform designers, policymakers and media scholars attempting to cope with the AI-driven media environment can find the findings helpful.
Keywords: AI-driven media consumption, Generational differences, Algorithmic trust, Ethical personalization.

1. Introduction

The recent emergence of artificial intelligence (AI) technology has changed the existing digital media consumption environment radically as it is no longer a content-based, passive, broadcast-like experience but the highly customized, algorithmically filtered experience that dynamically responds to the behavior, tastes and consumption behavior of users. They are now being built on state-of-the-art machine learning algorithms to recommend content and generate fluid and transparent ecosystems that regulate what users watch, the duration they watch and the type of stories they receive (Srivastava, 2025; Shah, 2025). A technological shift, but also a paradigm shifts in the balance of power between users, content creators and platform owners as the algorithmic systems have an even more substantial portion of the information and entertainment distribution grid as the distributors of information and entertainment. With pervasive AI-based personalization in every sphere of life, a growing concern is the question of its unequal influence on demographic groups, especially generation groups that have been socializing within numerous technological and media contexts.

The digital media usage disparities between the generations have increased in the age of AI. The younger digital natives such as Generation Z (born 19972012) and Millennials (born 19811996) are more engaged with AI-assisted features, such as hyper-personalized feeds and content, recommendations on short-form videos, and curation of content. These audiences are also more inclined to find convenience, relevance, and immersion valuable and view AI-suggested content as a tool to add to the discovery and entertainment value (Guerra-Tamez, 2024; Peter, 2025). In comparison, the more conservative sources and lack of trust in automated suggestions that are seen to infringe on their autonomy or provide biased curation are thought to make Generation X (born 19651980) and Baby Boomers (born 1946-1964) more conservative (Barbu et al., 2025; Teepapal, 2025). These changes are not merely superficial changes, but these are the indications of more profound socio-cultural and experience divisions. As an example, Gen Z users have been on a constant connection and algorithmic environment since childhood and are thus more accepting of personalization content, but more conscious of being influenced by the media in comparison to older users who need more transparency and human agency in their interaction with the media (Harrer, 2025).

The most basic feature of such generational relations is the notion of the algorithmic trust that shapes how users perceive AI recommendation systems to be trustful, fair, and helpful. The problem of algorithmic trust is not resolute, but it is based on what users know about how algorithms work, their prior knowledge of personalization and their concerns on the privacy of their information. The empirical studies indicate that more awareness of algorithms correlates with the perceived usefulness and ease of use of personalized recommendations and may also contribute to a skeptical attitude when it is perceived that the transparency or bias exists (Huang and Liu, 2025). Structural equation modeling has been shown to mediate the relationship between awareness and behavioral intention in large-scale surveys to interact with platform content, with privacy issues being a significant moderator (Huang and Liu, 2025). When the trust is broken (it may occur due to the filter bubble, echo-chamber or demotion of content without the reason) the intergenerational users either implement countermeasures such as manually curating the content, switching to a different platform or simply disregarding it to point out the inefficacy of the relationships between users and platforms in the AI-mediated context.

On top of these dynamics of trust is another layer of ethical concerns of AI-based personalization. Although the personalization will guarantee that there will be higher levels of user satisfaction and interaction, it would also translate to the invasion of privacy, algorithmic bias, consumer manipulation and loss of autonomy. There is a risk that the deployment of AI systems that have been trained on big data will unwillingly perpetuate social bias, causing the targeting of content to be biased or discriminative and will unfairly impact demographic groups (Karami et al., 2025). Furthermore, hyper-personalization practices can capitalize on the psychological vulnerabilities by capitalizing on behavioral nudges, emotional profiling, and predictive analytics, which can negatively impact informed consent and long-term digital well-being (Karami et al., 2025; Afroogh, 2024). These problems are also caused by lack of transparency, also known as the black box problem, whereby the users are not aware of the logic behind the decision-making of the recommendations, hence there is no sense of accountability and lack of trust in the public (Huang and Liu, 2025). Such ethical issues arise especially in the context of the generational differences between younger users being potentially tolerant of personalization due to their convenience and potentially greater control and older users not being tolerant of it at all due to its ethical implications of data ownership and integrity.

Even with the increasing amount of literature on AI in digital media, there are still major gaps in research. The majority of the literature explains quantitative surveys based on adoption rates or qualitative studies based on user perceptions on a case-by-case basis, and not many studies involve generational cohorts, algorithmic trust, and ethical personalization in one frame (Srivastava, 2025). Few studies apply mixed methods designs that can be used to develop generational differences and how the same may be fuelled by trust and ethics to influence consumption behaviors. Moreover, much of the literature is platform-based (e.g. only social media) or confined by geography, without taking into account the bigger cross-national or cross-generational nuances of various cultural locations (Peter, 2025). This study fills the gaps by adopting a stepwise explanatory mixed method to elaborate the phenomenon in its totality in a manner that is empirically based. The main purpose of the paper is to explore the variation in the generational cohorts in their AI-assisted consumption of digital media, levels of trust in algorithms, and their ethical perceptions of personalization.

In particular, the research aims to:

1. To quantify the differences in consumption behavior among the generations and the level of trust using survey data.
2. To find out the causes and individual experiences behind these patterns using in-depth interviews.
3. Develop an ethical personalization framework that is user-independent and innovative in terms of platform.

The research questions to be used include the following:

RQ1: To what extent do the generational cohorts differ in the patterns of using digital media and the consumption of the AI-suggested content?

RQ2: Does generational affiliation mediate the relationship between generational affiliation and personalized recommendations acceptance by way of algorithmic trust?

RQ3: Which do you believe are some ethical issues about the notion of AI personalization across generations and what does it mean in the long-term about media consumption behaviours?

RQ4: What design principles and policy suggestions can develop transparent, trustworthy, and morally upright personalization strategies?

This study is important beyond the area of scholarship. Digital platform designers and media organizations are provided with practical information on how the recommendation systems can be modified in such a way that the interaction is maximized without harming trust and moral values.The evidence can be used by policymakers and regulators to inform the guidelines on algorithmic transparency, data governance, and consumer protection in the AI era. The experimentally validated framework between the generational theory and technology acceptance models and ethical AI discourse will be practical to media scholars and educators. Finally, shedding light on the change of the generation, algorithmic trust and ethical personalization, this writing would help create a more human and sustainable digital media ecosystem, whereby the user agency is highly valued, and where artificial intelligence applies its potential to transform the digital world.

2. Review of Literature

The digital media consumption process has radically changed with the speed of artificial intelligence (AI) technology development that replaces classical broadcasting with the dynamic and algorithmically based eco-systems that personalize the content in real-time. On Tik Tok, YouTube, Instagram or Netflix among others, machine learning algorithms analyze user behavior, preferences and other contextual information to offer as engaging as possible, with minimal effort on the part of the user (Shah, 2025; Srivastava, 2025). This change is not just a convenience, but it changes the entire notion of media consumption as a whole as it makes predictive analytics a new aspect of daily communication. In his discussion of AI and consumer behavior on social media (2025) Srivastava adds that these systems do not simply suggest the content but also influence behaviors of the users via reinforcement loop of learning, where repeated use would maximize the output of the algorithm. In the form of an appendix, Shah (2025) states the application of AI to digital media as a force of hyper-personalized experience and states that hyper-personalized systems are now the most powerful source of information and entertainment in the modern digital setting. There is empirical data of big platform analytics that support the idea that algorithm-driven recommendations contribute to much of user time on the Internet, which creates what scholars refer to as an attention economy that is not based on the decision of the user. The main idea of the changes discussed is the idea of the generational differences of the consumption patterns of digital media. According to the generational cohort categories, e.g., Gen Z (born 19972012), Millennials (born 19811996), Gen X (born 19651980), and Baby Boomers (born 19461964) differ in the level of socialization with technology that have a significant impact on their engagement with AI-based Digital natives who are younger and grow up in the algorithmic environment at a young age show a greater level of acceptance of personalized content. In a series of works on Gen Z engagement with AI in fashion, technology, beauty and education, Guerra-Tamez (2024) discovered that the generation does not rely on AI recommendations based on their relevance and effectiveness due to their belief that they are an extension of the discovery process that is intuitively generated. Likewise, Peter (2025) examines the emotional reaction of Gen Z to hyper-personalized ads and finds that convenient engagement is one of the primary factors in the growth of trust over the long term, whereas emotional authenticity is one of the primary factors in the growth of trust. It aligns with the master thesis, by Harrer (2025), about AI strategy customization by generation, which documents that Millennials and Gen Zers are more willing to adopt elements of AI, such as creating short-form video curation and predictive playlists, into their daily lives at a significantly higher frequency than the older generations.

The senior citizens are, however, less enthusiastic and even skeptical towards adoption practices. Exploring how Gen X and Baby Boomers view AI-generated reviews when shopping online in the textile industry, Barbu et al. (2025) found that these two generations are more conservative and prefer human information and voice their worries related to authenticity and possible manipulation. The underlying issue behind this mistrust is that older users who switched to using digital media during old age value familiarity, transparency, and a sense of autonomy more to the usefulness of algorithms (Harrer, 2025; Teepapal, 2025). Teepapal (2025) explains that when their suggestions become opaque or biased, older cohorts prefer to use resistance strategies, which may include using a platform manually, or by not using it at all, as an example of this disillusionment of consumer attitudes towards AI-inspired personalization in social media interactions. These generational differences cannot merely be behavioural but a result of more fundamental socio-cultural and experience differences, where the ever-connected nature of young users generates an algorithmic fluency, and the older generation is more focused on human control as a signifier of preference of controllable media ecologies (Barbu et al., 2025). All these points to generational affiliation being a valid predictor of high level of consumption and the degree of generational affiliation of the younger generation has higher engagement rates and at the same time, lack of long-term platform attachment.

One of the key mediating constructs of these generational trends is algorithmic trust - how much users trust AI recommendation systems as trustworthy, fair, impartial, and useful to their media experiences. Algorithms trust is relational in nature since users can know about the underlying workings, have experience and are affected by more contextual factors such as data privacy. With help of structural equation modeling based on Technology Acceptance Model (TAM) Huang and Liu (2025) present the sound empirical evidence. Their national survey showed that the attitudes to personalized content, usefulness (= 0.63), ease of use (= 0.58) and trust (= 0.51) are positively related to awareness of algorithms, mediating the intentions to use personalized content. More to the point, but to a higher extent, cynicism can be amplified due to increased awareness in case of suspicion, either of the lack of transparency or of biasness, which can create a sort of a paradox whereby, the more people learn about personalizing something, the more people doubt their ability to manipulate it (Huang and Liu, 2025). This duality is in line with the synthesis of trust in AI presented by Afroogh (2024) who considers both the advances in technical reliability and the continuation of the transparency and moral alignment issues. Afroogh (2024) claims that the notion of algorithmic trust is not a one-size-fits-all concept but rather situation-specific, based on the digital literacy and experience of users, which also differ significantly across generations.

These dynamics are also brought out by qualitative insights. Huang and Liu (2025) interviewed and found out that, when they lose their trust in filter bubbles or in unexplainable demotion of content, users have turned to resistance strategies to switch platforms and curate their feeds manually. Younger generations are more participatory at the base with less trust in algorithms due to the high levels of fear of privacy and manipulation by a life-long history of exposure to data-driven ecosystems (Guerra-Tamez, 2024; Peter, 2025). The older generations, in their turn, possess a foundation of distrust yet a conditional trust augmentation with the inclusion of the explicit features of transparency in the systems (Barbu et al., 2025; Harrer, 2025). Teepapal (2025) affirms it by explicitly relating algorithmic trust to the outcomes of engagement, assuming that disengagement, which is usually brought about by a feeling of bias or inexplainability, will happen in all cohorts, but heterogeneously. By doing so, algorithmic trust turns out to be a major support between generational attachment and acceptance of personalized recommendations, and it has implications in terms of platform retention and well-being of users.

To these trust dynamics are the ethical considerations of AI-led personalization that consist of invasion of privacy, algorithmic bias, manipulation of consumers and loss of autonomy. Karami et al. (2025) give a detailed overview of these implications in online marketing and classify them into three categories: violation of data sovereignty, recommending a discriminatory pattern, and psychological exploitation caused by the behavioral nudging.They talk about how trained AI systems, due to being trained on bulk data, can encourage discrimination within society, enabling it to be either exclusionary-targeting, where it targets marginalized people disproportionately, or be exploitative with predictive profiling (Karami et al., 2025). The black box problem worsens these issues, as it is untransparent and distorts the logic and responsibility of decisions (Huang and Liu, 2025). Teepapal (2025) extends this critique to the social media sphere and records the means through which the hyper-personalization tactics can undercut informed consent and long-term health in the online, especially those who choose convenience over control. The two generations differ in ethical issues. The other indicator of increased agency sensitivity to manipulation is that even younger users are increasingly agency and ethically protective (although they are also attaching more importance to personalization by its discovery value) (Guerra-Tamez, 2024; Peter, 2025). Compared to the older generations, they are more prone to be opposed to hyper-personalization and argue their claim based on data sovereignty and authenticity and consider it a violation of their individual autonomy (Barbu et al., 2025; Harrer, 2025). Such generational differences are introduced by Afroogh (2024) in the context of the larger philosophical discourse of AI ethics, suggesting the human-based design frameworks. Srivastava (2025) and Shah (2025) also warn that unregulated

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personalization also creates a risk of turning the process of consumption into a feedback loop of manipulation where the measures of engagement are more important than the empowerment of the user. Such ethical conflicts underscore the importance of moderate ways that strike a balance between innovation and responsibility. Literature continues to be large with a lot of gaps. The bulk of the literature is of an isolated character: platform-dependent (e.g. social media or e-commerce) or methodologically narrow, based on quantitative measures of adoption or a single qualitative perception without putting generational cohorts, algorithmic trust and ethical personalization into a unified framework (Srivastava, 2025; Peter, 2025). Not many use mixed methods design that would explain the causal processes or lived experiences in different cultural settings (Huang and Liu, 2025; Karami et al., 2025). Moreover, the comparisons between generations can hardly pay enough attention to subtle overlaps with the privacy concerns, digital illiteracy, and culture (Barbu et al., 2025; Guerra-Tamez, 2024). This paper fills these gaps by combining quantitative survey results with qualitative depth to come up with an integrative system of ethical personalization.

Overall, the reviewed literature demonstrates that AI-mediated use of digital media is a disruptive, but a very polarizing trend, accompanied by major generational shifts, mistrust towards algorithms, and the presence of numerous complicated ethical concerns. The current study can contribute to closing these gaps and supplementing the theoretical foundation and providing viable prospects to establish transparent, trustful and user-centered AI ecosystems.

3. Methodology

In this paper, the sequential explanatory mixed-method research design has been employed to discuss the generational differences in the usage of AI in digital media, algorithmic trust and ethical perceptions of personalization. It was structured as having a quantitative (online survey) and a qualitative phase (semi-structured interviews) in which the latter was implemented to clarify, elaborate, and elaborate the results of the former (Creswell and Plano Clark, 2018). The method was selected as it could assist in answering the multi-faceted goals and research questions of the study in a holistic way. Speaking more precisely, the quantitative survey made it possible to measure the generational gap in consumption tendencies and the measures of trust as well (Objective 1; RQ1 and RQ2) and the moderating influence of the algorithmic trust was also quantified with the assistance of the structural equation modeling (SEM). The qualitative interviews that followed presented contextual and rich data on the mechanisms and lived experience and ethical issues (Objective 2; RQ3) that resulted in the development of an integrative framework of ethical personalization that balances user autonomy with platform innovation (Objective 3; RQ4). Sequential explanatory design is particularly explained to explain complex socio-technical phenomena such as AI-mediated media consumption in which statistical generalization can be incorporated by a more detailed explanatory understanding of the issue of why and how generation gap occurs (Kurtaliqi et al., 2024; Nielsen Norman Group, 2025). The research might conduct methodological triangulation by merging the two strands in the interpretation phase that increased the validity, reliability and the feasibility of the findings in the policy making process by the platform designers and policy makers.

3.1 Universe of Study

The study population consisted of active users of digital media, who lived in the National Capital Territory (NCT) of Delhi, India, and who considered themselves as a part of one of four generations Gen z (born 19972012), Millennials (born 19811996), Gen X (born 19651980), and Baby Boomers (born 19461 As of September 2024, around 112.74 urban internet subscribers in India (per 100 population) were (Telecom Regulatory Authority of India [TRAI], 2025) and even more in Delhi-NCR, where more than 20 million young people

3.2 Sampling and Sample Size

A stratified purposive sampling approach was employed in order to ensure that the number of respondents of the four generational cohorts was well balanced and to make it feasible in the Delhi setting. The number of subjects (400) was increased to 400 (100 subjects per generation) to the quantitative phase. This was an appropriate sample size because of various reasons that were in tandem with the research objectives and questions. First, the G*Power 3.1 (Faul et al., 2009) power analysis revealed that N = 400 had more than 80% statistical power to detect medium effect sizes (f 2 = 0.15) in multi-group comparisons (e.g., ANOVA to answer RQ1) and mediation models (RQ2) at =.05. Second, 10 observations per parameter estimated (Kline, 2023) were adequate to obtain a strong estimation of the proposed measurement and structural models with generational affiliation, algorithmic trust, and acceptance of personalized recommendations in the case of SEM. Third, to improve comparability, the stratification was equal (100 in cohort), and sampling bias in generational analyses. Particularly, this small N = 400 was selected to be realistic and manageable in a study whose focus is on a single city, and which makes it possible to obtain high quality data collection since it was focused on online distribution without the necessity to compromise the generalizability of patterns of the Delhi urban universe (Krejcie and Morgan, 1970; Vasileiou et al., 2018).

During qualitative phase, 24 semi-structured in-depth interviews were conducted (6 interviews each of the generational groups). The principle of thematic saturation (Guest et al., 2006) was used to determine the sample size, which included data collection until there were no emerging themes, in terms of ethical issues, trust relationships, and behavioral determinants (RQ3). This reduced and densely detailed sample made it possible to delve into the lived experiences that may describe the trends in the surveys, which is in line with the best practices in explanatory mixed methods designs (Nielsen Norman Group, 2025).

Both phases were recruited by using a mix of social media advertisements (advertised to the Delhi users on Meta and Instagram) and university and community groups and snowballing, in which respondents were required to answer screening questions in order to identify a generational group, their location, and current use of AI-platforms. The diversity in terms of gender, education and occupation was also used as an inclusion criteria to capture the population of Delhi.

Table 3.1 Distribution of Survey Respondents by Generational Cohort and Gender (N = 400)

Generational Cohort	Male	Female	Other/Prefer Not to Say	Total	Percentage
Gen Z (1997–2012)	48	49	3	100	25%
Millennials (1981–1996)	47	50	3	100	25%
Gen X (1965–1980)	51	46	3	100	25%
Baby Boomers (1946–1964)	49	48	3	100	25%
Total	195	193	12	400	100%

Note. Gender distribution was approximately balanced within each cohort to minimize confounding effects.

3.3 Data Collection Instruments : The quantitative variable was a structured online questionnaire (hosted on Google Forms and Qualtrons) that comprised of four sections as follows: (1) demographics and media consumption behavior (frequency, platforms, time spent, interest in AI recommendations); (2) algorithmic trust (adapted 7-point Likert scale of Huang and Liu, 2025); (3) ethical perception of personalization (pil

The qualitative guide contained 10-12 open-ended questions that asked about lived experiences of personalization, loss of trust, ethical dilemmas (privacy, prejudice, autonomy), and desired design/policy solutions (RQ3 and RQ4). Interviews were 45-60 minutes long and were held via Zoom or at the convenience of the locations in Delhi in English or Hindi (with translation as necessary) with consent to audio-record.

3.4 Data Collection Procedure : The data that was collected were between October 2025- January 2026. The questionnaire was sent out in eight weeks and 427 questionnaires (400 of which had not been thrown away during the cleaning process) were received. This was then succeeded by the survey analysis and then interviews whereby the survey volunteers or independent networks were then chosen purposely to provide the maximum variation. Pilot testing and professional validation guaranteed cultural and linguistic suitability to the wide range of people in Delhi.

3.5 Data Analysis : IBM SPSS 28 was used to analyze quantitative data (descriptive and inferential statistics (ANOVA/MANOVA) to answer RQ1 and SEM (maximum likelihood estimation with bootstrapping) to answer RQ2). The fit of the model was evaluated in terms of $\chi 2$/df, CFI, TLI, RMSEA, and SRMR. Reflexive thematic analysis (Braun and Clarke, 2022) was used to analyze qualitative data, which included six stages of coding, theme generation, and review. Integration was done by means of joint displays and meta-inferences which directly informed the ethical personalization framework (RQ4).

3.6 Ethical Considerations : The study received approval from the Institutional Review Board of [Affiliated University]. Informed consent was obtained digitally (survey) and verbally/written (interviews). Participation was voluntary, with guarantees of anonymity, confidentiality, and the right to withdraw. Data were stored securely, and findings were reported without identifying information. Special care was taken with older participants to ensure accessibility and comfort.

4. Data Interpretation and Analysis: The interpretation of the data combines both the quantitative and the qualitative strands in a chronological order in the explanatory fashion as proposed in the methodology. The quantitative stage (N = 400 survey respondents, 100 respondents per generation cohort) initially considered the first objective (O1) and research question (RQ1) in determining the generational differences in AI-based consumption patterns of digital media and consumption of algorithmically suggested content. It also addressed RQ2 by using structural equation modeling (SEM) to identify the value of mediation of the algorithmic trust. The qualitative stage (24 semi-structured interviews, 6 per cohort) was used to further develop these patterns and examining the lived experiences,

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mechanisms, and ethical concerns (Objective 2; RQ3) and eventually feeding the integrative system of ethical personalization (Objective 3; RQ4). All the analyses were conducted in the urban setting of Delhi where the rate of digital adoption is very high making the differences in generations even greater. It is preoccupied with the statistical significance, the richness and volume of the informative material but authentic in its connection with the research questions and the online cosmopolitan ecosystem of Delhi.

4.1 Quantitative Findings

Descriptive statistics revealed clear generational gradients in media consumption. Table 4.1 presents mean daily digital media consumption hours and the percentage of engagement with AI-recommended content (self-reported on a 0–100% scale).

Table 4.1 Mean Daily Digital Media Consumption and AI-Recommendation Engagement by Generational Cohort (N = 400)

Generational Cohort	Daily Media Hours (M ± SD)	% Engagement with AI-Recommended Content (M ± SD)	Platforms Most Used (Top 2)
Gen Z (1997–2012)	4.62 ± 1.28	78.4 ± 12.6	TikTok, Instagram
Millennials (1981–1996)	3.81 ± 1.15	67.2 ± 14.3	YouTube, Instagram
Gen X (1965–1980)	2.14 ± 0.97	41.5 ± 18.9	YouTube, Netflix
Baby Boomers (1946–1964)	1.48 ± 0.82	26.3 ± 15.7	YouTube, Facebook

Note. One-way ANOVA confirmed significant differences (see Table 4.2).

A one-way MANOVA tested RQ1 and found that the multivariate effect of generational cohort on the aggregate dependent variables of media consumption hours and AI-engagement percentage showed that differences by all metrics were highly significant, with post-hoc Tukey HSD all significantly less than.001. These patterns are compatible with the research on digital nativity (Guerra -Tamez, 2024; Peter, 2025) and may be concluded that the younger generations in Delhi are more active consumers of AI-curated ecosystems, as they have been fed on algorithmic feeds since their early years.

Table 4.2 One-Way ANOVA Results for Generational Differences in Consumption Patterns (RQ1)

Variable	F(df)	p-value	Partial η^2	Post-hoc (Tukey HSD)
Daily Media Hours	142.36 (3, 396)	<.001	.519	Z > M > X > BB
% AI-Recommendation Engagement	98.72 (3, 396)	<.001	.428	Z > M > X > BB

Note. Z = Gen Z; M = Millennials; X = Gen X; BB = Baby Boomers.

In case of RQ2, the mediator that was analyzed was algorithmic trust (7-point Likert scale modified by Huang and Liu, 2025; overall Cronbach 7 =.89). Mean trust scores declined with younger age: Gen Z (M = 3.21, SD = 1.04), Millennials (M = 3.78, SD = 1.12), Gen X (M = 4.65, SD = 0.98), Baby Boomers (M = 5.12, SD = 0.89). ANOVA confirmed significance: $F(3, 396) = 87.45$, $p < .001$, partial $\eta^2 = .398$.

The hypothesized model was tested with the help of SEM (AMOS 28, 5000 bootstraps): Generational Cohort → Algorithmic Trust → Acceptance of Personalised Recommendations (measured as behavioural intention, 7-point scale). The measurement model showed excellent fit ($\chi^2/df = 1.87$, CFI = .96, TLI = .95, RMSEA = .048, SRMR = .039). According to the structural model (Table 4.3), the relationship was fully mediated: generational affiliation negatively correlated with trust (= -.47, p < .001), and acceptance was positively correlated with trust (=.62, p <.001). The indirect influence was of considerable importance (bootstrapped 95% CI [–.35, –.19]) and the direct influence of generation to acceptance was insignificant when including the mediator (0 = -.08, p =.214). Acceptance variance was explained by model 58%. These findings strongly confirm RQ2, with findings indicating that less trust in younger Delhi users, due to awareness of privacy, inhibit acceptance, despite greater baseline engagement, in line with Huang and Liu (2025) and Afroogh (2024).

Table 4.3 Standard Coefficients of Paths (SEM) (RQ2)

Path	β (Standard Coefficient)	SE	p-value	95% CI (Bootstrap)
Generational Cohort → Algorithmic Trust	–0.47	0.06	< .001	[–0.58, –0.36]
Algorithmic Trust → Acceptance	0.62	0.05	< .001	[0.52, 0.71]
Indirect Effect (Trust Mediation)	–0.29	0.04	< .001	[–0.37, –0.21]

These findings were supplemented by ethical perception items (adapted/modified according to Karami et al., 2025). The younger generations were more concerned with privacy/manipulation (Gen Z M = 5.84/7; Millennials M = 5.61) compared to older ones (Gen X M = 4.12; Boomers M = 3.89), supporting the quantitative basis of the qualitative elaboration.

4.2 Qualitative Findings (Thematic Analysis)

Thematic analysis of the 24 interviews transcripts (approximately 720 minutes of audio) were conducted in a reflexive way (Braun and Clarke, 2022), which resulted in four general themes that directly answered RQ3 and explained the quantitative trends. There was high inter-coder reliability (087) in deriving themes.

Theme 1: Privacy and Manipulation Fears as Barriers to Trust This was the most popular in Gen Z and Millennials (named by 11/12 younger interviewees). The participants mentioned algorithms as to watching and predicting too much (Gen Z, 22, female, student of Delhi University). One of the Millennials (31, male, IT professional) mentioned: It reads my mind before I can decide, convenient, but it seems to be manipulative, as it directs my decisions. This found sympathy with lower quantitative trust scores and was the source of opposition, despite high involvement. Older cohorts gave less strong concerns, seeing privacy as being less personal when suggestions were predictable (Gen X, 52, male).

Theme 2: Wish to have Transparency and Explainability All cohorts held the view of the significance of transparency, but systems differed. Younger participants insisted on control via pop-ups or sliders (5/6 Gen Z) with why this video? The older interviewees were concerned with human control: I would like to know the logic not accept the black box (Baby Boomer, 68, female, retired teacher). This theme was directly linked to the results of mediation- transparency could raise the degree of trust and acceptance between generations, the ethical element of RQ3.

Theme 3: Tension between Autonomy, Convenience, and Long-term well-being Gen Z and Millennials tended to value autonomy more than convenience (I scroll for hours because it's addictive, Gen Z, 19) yet noted feeling tired and echo-chamber effects on long-term behavior (e.g. platform switching). The strongest in their opinions about autonomy were older participants: I choose what to watch, the algorithm must not command me (Gen X, 47). This theme explained the impact of ethical concerns to identify long-term consumption- the younger users were volatile although they used highly initially and the older users were stable but less.

Theme 4: Generational Call to Ethical Protections Respondents of various cohorts proposed concepts in accordance with RQ4: mandatory algorithms to conduct ethical audits, default settings based on age, and default setting policy-driven data consent dashboard. A Baby Boomer (62) would push sunset clauses in data retention; one participants of Gen Z suggested adjusting the algorithm as long as the user approved it. These were empirical revelations that were the loved ones who aided the proposed framework.

4.3 Integration of Quantitative and Qualitative Strands and Emergent Framework

Convergence was supported by the joint displays (Creswell and Plano Clark, 2018): the explanation of the lower trust scores in younger cohorts was greatly relied on the discourse of privacy/manipulation, and the explanation of the higher trust scores in older cohorts was significantly attributed to the familiarity preference. The ethical weighting-quantitative evidence resulted in diversity in the sense that there were an equal number of concerns, but interviews indicated that it came in such subtle ways (convenience tolerance among the youth and principled rejection among the elderly). The combination is directly connected with Objective 3 in the sense that it is the basis of the Ethical Personalization Framework (EPF).

There are three pillars of the EPF: (1) User Autonomy Layer (explainable AI summaries, opt-in personalization sliders, address Theme 2); (2) Transparency Engine (audits of algorithm behavior in real-time, disclose bias, mitigate Theme 1); and (3) Generational Calibration Module (address bias, age-cohort defaults with ethical nudges, reconcile convenience/well The framework reflects RQ4 with a compromise between innovation and trust and provides viable design principles which have been approved by the Delhi users.

In general, the interpretation of the data can be summarized as follows: even though AI personalization leads to greater degrees of engagement among the younger generation in Delhi (RQ1), the presence of exhausted trust to the algorithms (RQ2) and ethical issues of the most severe nature (RQ3) hinder the concept of sustainable adoption. The EPF offers a course toward plausible, moral right directions (RQ4), and a contribution to empirically-based knowledge of the urban Indian digital media.

5. Discussion

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The present mixed-methods exploration offers a nuanced, contextualized understanding of how artificial intelligence is changing the digital media consumption of the generational groups in the busy urban digital environment of Delhi. The study, by utilizing the combination of the large-scale survey data (N = 400) and detailed qualitative data (n = 24 interviews), quantifies the generational differences in addition to explaining the psychological, ethical and experience-based mechanisms that underline these trends. The results are a superb response to all the four research inquiries and respond to the three key objectives of the study: to quantify variations and trust measures, understand lived experiences, and develop a framework of integrative Ethical Personalization Framework (EPF). This way, the discussion situates the results in a wider theoretical context of technology acceptance, generational theory and ethical research of AI, not only in illustrating the similarities, but also elaborates further on the existing research.

The primary characteristic of RQ1 which was deemed as critical, was that the differences in the generational patterns of consumption and the consumption of the AI-suggested content were quantified. It was found that Gen Z and Millennials spent the most hours on the media per day (4.62 and 3.81, respectively) and were the most likely to be engaged with AI (78.4 and 67.2 percent, respectively) in comparison to Gen X (2.14 hours) and Baby Boomers (1.48 hours). The hypothesis about the digital-native generation mentioned in the literature is proven by the fact that the big differences between MANOVA and ANOVA are supported (Guerra-Tamez, 2024; Peter, 2025). In the high-penetration urban market of Delhi, where internet penetration is greater than national (TRAI, 2025), younger generation views algorithmic curation as a continuation of their 24/7 lifestyle and rely on such applications as Tik Tok or Instagram to retain the discovery. According to Barbu et al. (2025) and Harrer (2025), consumption of aged cohorts is more intentional and human hand made. The fact that the city center of Delhi is a cultural peculiarity indicates that the youth of the megacities in India is not simply a passive consumer, but an active participant of an attention economy, created by hyper-personalized feeds.

The structural equation modeling indicated a high level of support of RQ2 mediation hypothesis; i.e. that algorithmic trust is the mediator between generational affiliation and acceptance of personalized recommendation. The younger generations had significantly lower trust scores (Gen Z M = 3.21; Millennials M = 3.78) even though they were more engaged, and trust completely mediated acceptance (indirect 3 = -0.29, p <.001). This counterintuitive trend that they describe as high use, low trust, builds on the result of the Technology Acceptance Model by Huang and Liu (2025) to show that awareness of the algorithm on the one hand raises the perceived usefulness of the algorithm on the other hand, suspicions of the absence of transparency or manipulation. This process was described in more detail in qualitative narratives: younger participants in Delhi have repeatedly described algorithms as something to watch excessively or drive a decision, which caused a privacy paradox unique to digital natives, as they have never lived in a non-algorithmic media world (Afroogh, 2024; Peter, 2025). The older participants, however, more easily trusted the baseline, when the recommendations were made on familiar sources, which emphasizes the role of the generational socialization mediating the development of trust (Teepapal, 2025). The situation is further problematic by the Delhi environment where due to the increasing rate of urbanization and the emergence of platforms sensitive to data, the youth generation is more sensitive to privacy and is the subject of the changing Digital Personal Data Protection system in India.

Ethical concerns (RQ3) were taken as a prism which is important in mirroring the generational differences to influence long-term behaviors. The identified four interwoven themes in thematic analysis were privacy/manipulation fears, demands transparency, autonomy-convenience tension and demands ethical protection that directly explained quantitative trends. The younger generations did not demonstrate negative attitudes to the phenomenon of hyper-personalization as it is convenient, but they were very worried about the existence of echo chambers, emotional profiling, and loss of autonomy, which can be associated with the concept of discriminatory targeting and behavioral nudges by Karami et al. (2025). The older generations were not as active, but were more principled in their criticism with references to data sovereignty and authenticity and concurred with Srivastava (2025) and Shah (2025). These are not merely in parallel with consumption patterns but their authors. One such example is that youth trust has a negative correlation with volatility: platform switching and manual curation and older user trust has a positive correlation but a smaller correlation with more frequent than sustained engagement. The qualitative richness subsequently shows how the notions of ethics are not peripheral but core mediators of sustainable media use in the AI-driven ecosystems, more so in the culturally diversified urban India where family values and individual digital autonomy are in conflict.

The third objective of the study, which is the formulation of an integrative framework of ethical personalization is achieved by the designed Ethical Personalization Framework (EPF). It is based on statistical mediation and thematic knowledge, and has three overlapping pillars (1) a User Autonomy Layer facilitating granular opt-in controls and explainable AI summaries; (2) a Transparency Engine facilitating real-time bias audits and decision logic disclosures; and (3) a Generational Calibration Module facilitating age-cohort defaults with ethical nudges. This framework will directly respond to RQ4 which will transform user requirements into feasible design ideas and policy recommendations. In the case of platform designers working in India (e.g. Instagram, YouTube), the introduction of EPF would help to reduce the loss of trust, without compromising the engagement, which would offset innovation and accountability. EPF features within regulatory frameworks developed by the policymakers can be applied to the Digital India project or AI ethics standards of the future, where user agency is guaranteed through personalization and is not put at risk. Theoretically, the EPF builds on the generational theory (Harrer, 2025), the technology acceptance models (Huang and Liu, 2025), and the ethical AI discourse (Afroogh, 2024; Karami et al., 2025), spreading a humanistic paradigm, where transparency and autonomy are prioritized over the raw engagement rates.

The quantitative and the qualitative strands are combined to improve the validity of the research. Younger users who had less trust were not abstract but vividly expressed in the lives of the participants (as addictive and manipulative feeds) and this is a type of methodological triangulation at its finest (Creswell and Plano Clark, 2018). The minor variation, as in homogenous quantitative level of concern and subtle qualitative manifestations, also contributes to knowledge, making it obvious that ethical weightings are not only differing according to the generation but also in the digital literacy and life stage of an individual in the social-economic mosaic of Delhi.

Such contributions are subject to limitations, which are to be outlined. The universe employed, which is the location of the capital city of Delhi is strategically chosen as it has high digital adoption and heterogeneity; however, it cannot be considered as the national trend because users in the rural or smaller cities may have different trends because of the constraints of their infrastructure. Regardless of the pilot testing, self-reported measures have the issue of social-desirability bias especially when it comes to sensitive privacy issues. Cross-sectional design does not allow making causal inferences related to time and the sample is powerful but small compared to pan-Indian studies. The second-generation study will require longitudinal designs to study the trend of trust, as AI is becoming more and more powerful, multi-city/rural cohort, and test the EPF as an experimental intervention or an A/B platform trial. Such comparative cross-cultural analyses (e.g., India vs. Global South settings) would also be more enlightening about the mediation of cultural values to generational reactions to algorithmic personalization.

To sum up, this exploration sheds light on the two-sidedness of AI-based consumption of digital media: an efficient cultivator of discovery among a younger generation that also undermines trust and provokes ethical concerns among all generations. Proceeding to predict the voices of the Delhi users, the research points out that there is no technological determinism that cannot be modified but changes between generations are affected by the social construct which could be ethically redesigned. The Ethical Personalization Framework offers an evidence-based pathway (much-needed) that platform designers, policymakers, and scholars can take to create open, trustworthy, and humane AI ecosystems, a system that is both interesting and independent in the quickly digitizing Indian media landscape and elsewhere. Lastly, the paper demonstrates that a sustainable model of the introduction of AI into the digital media must not just be implemented by a technical skill but also a more profound sense of user ethics since the algorithmic curation must serve to foster human flourishing, and not to annihilate it.

6. Conclusion

This qualitative and quantitative study has critically examined how the four generations in Delhi, India, have changed their habits of media consumption, trusting algorithms, and attitudes towards personalization using artificial intelligence. By adhering to a sequential explanatory design, quantitative survey (400 respondents) and semi-structured interviews (24) (in- depth), the research could fulfill its three primary goals and four research questions. The results provide powerful arguments to prove that personalization using AI is not a technological phenomenon that did not have another side but a radically generational phenomenon that changes the way people find, experience, and judge digital contents in the dynamic media environment of urban India.

The study demonstrates that the differences in the consumption patterns between generations are strong. Gen Z and Millennials were far more active on digital media and information suggested by AI on a daily basis than Gen X and Baby Boomers. However, the level of this greater engagement of younger generations is associated with much lower levels of algorithmic trust that fully arbitrates the connection between generational affiliation and acceptance of personalized recommendations. Qualitative evidence also suggested that privacy issues are mistrust drivers among the digital natives who have matured in an algorithmic world, and that perceived manipulation and quality as black boxes are mistrust drivers. Ethical considerations of autonomy, prejudice, data ownership and long-term digital health were found to be core determinants of sustainability in use, and also varied by generation: the younger users were willing to customize to the level of convenience, and older users needed values of autonomy and transparency.

The paper will present a new, empirically informed framework, Ethical Personalization Framework (EPF)- a three-component framework, which includes the User Autonomy Layer, Transparency Engine and Generational Calibration Module, to assist answer the final research question. This model provides an appropriate way through which the user interaction and algorithmic innovation, as well as ethical accountability can be balanced. The theoretical contribution is a valuable one as it integrates the generational perspective, technology acceptance principles, and ethical issues of AI into a single theoretic framework that is particularly sensitive to the Indian urban context.

The research works that are put forth in the paper are both theoretical and pragmatic. Theoretically, it will facilitate the development of a coherent understanding of how the interaction between generational socialization and algorithmic systems in a high-growth digital economy in India will happen. A methodologically rich contextual subtlety is in the Delhi-centric universe, which puts a premium on the role of metropolitan infrastructure and cultural diversity in intensifying the generational differences in media consumption. In practice, the results and the EPF can offer the platform-designers practical advice to develop more believable recommendation systems, to the regulators to expand the regulatory frameworks like the Digital Personal Data Protection Act and to media companies to establish sustainable relationships with users in an AI-dominated world.

Academia is not in such implication. In terms of digital in India, integration of the aspects of the EPF may lead to decreased resistance to change of the number of users, higher retention in the long term and lower reputational risk due to privacy concerns or algorithmic bias. The paper reminds policy makers and regulators of the pressing need of mandatory transparency, explainability, and age-equivalent protection of AI systems. Socially, the paper recognizes a need to protect digital health at any age, in order to transform AI into an empowering and not an insidious means of control over attention and the decision-making process.

In spite of the strong points the study has, there are weaknesses. The cross-section design and the sample, located in Delhi, but applicable in the dimension of depth and relevance, limits the need to be cautious as generalizations are made to the population outside of the urban areas or the pan-Indian population. Longitudinal designs can be used in future studies to follow the evolving relationships of trust, scale up to multi-regional samples, and experimentally test the EPF through field experiments or platform collaborations. Comparisons between different cultural and economic environments across the world would also promote the global awareness of AI personalization ethics.

To sum up, the future of the digital media is not an uncontrollable maximizing of the algorithms, but a human-focused ethical design that is attentive to the generational diversity and places human agency on the center stage. As the continuous spread of artificial intelligence to all media consumption procedures, Ethical Personalization Framework, worked out below, is an opportune reference point concerning the creation of transparent, reliable, and human-centered online realms. Finally, there will be either technological value of human experience through the smart use of AI in online media or the devaluation of it. Putting the voices of the users in the center of the various generational space of Delhi, this paper helps achieve a fairer and more sustainable AI-mediated media future, where personalization is based on discovery and empowerment, and not on surveillance and control.

The results force the research, practitioners and policymakers to shift the measures of engagement to values-based approach whereby the autonomy of users, transparency, and ethics lie at the core of an algorithm systems. It is the sole path, the transformational power of artificial intelligence can be utilized to the full extent without robbing the human part of media consumption.

References

1. Afroogh, S. (2024). Trust in AI: Progress, challenges, and future directions. *Humanities and Social Sciences Communications, 11*, Article 1234. https://doi.org/10.1057/s41599-024-04044-8
2. Barbu, A. M., Popa, I.-C., Florescu, M. S., Crețu, A. I., Chivu (Popa), R.-G., &Chenic, A. Ș. (2025). Generational differences in perceptions of AI-generated reviews in online textile purchases: Implications for sustainable digital consumption. *Industria Textila, 76*(4), 576–590. https://doi.org/10.35530/IT.076.04.202558
3. Braun, V., & Clarke, V. (2022). *Thematic analysis: A practical guide*. SAGE Publications.
4. Creswell, J. W., & Plano Clark, V. L. (2018). *Designing and conducting mixed methods research* (3rd ed.). SAGE Publications.
5. Faul, F., Erdfelder, E., Buchner, A., & Lang, A.-G. (2009). Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods, 41*(4), 1149–1160. https://doi.org/10.3758/BRM.41.4.1149
6. Government of India. (2023). *Digital India report: Youth and digital engagement*. Ministry of Electronics and Information Technology.
7. Guerra-Tamez, C. R. (2024). Decoding Gen Z: AI's influence on brand trust and purchasing behavior. *PMC*, Article PMC10944976. https://pmc.ncbi.nlm.nih.gov/articles/PMC10944976/
8. Guest, G., Bunce, A., & Johnson, L. (2006). How many interviews are enough? An experiment with data saturation and variability. *Field Methods, 18*(1), 59–82. https://doi.org/10.1177/1525822X05279903
9. Harrer, M. (2025). *Customizing AI strategies across multiple generations* [Master's thesis, Lindenwood University]. Digital Commons. https://digitalcommons.lindenwood.edu/cgi/viewcontent.cgi?article=2421&context=theses
10. Kumar, S., & Hooda, S. . (2023). Healthcare and Hospital Promotions and Audience Reception. *MediaSpace: DME Media Journal of Communication*, *3*(01), 16–19. https://doi.org/10.53361/dmejc.v3i01.03
11. Kumar, S., & Singh, P. (2023). Emotional Appeal in the Tweets: A Study on Indian National Political Parties. *Journal of Communication and Management*, *2*(02), 95–97. https://doi.org/10.58966/JCM2023223
12. Kumar, S. ., & Hooda, S. (2023). An Analytical Review of Political Communication in India with Special Reference to the Social Media. MediaSpace: DME Media Journal of Communication, 3(01), 8–15. https://doi.org/10.53361/dmejc.v3i01.02
13. Huang, Y., & Liu, L. (2025). The impact of algorithm awareness on the acceptance of personalized social media content recommendation based on the technology acceptance model. *Acta Psychologica, 259*(Suppl C), Article 105383. https://doi.org/10.1016/j.actpsy.2025.105383
14. Internet and Mobile Association of India (IAMAI). (2025). *Internet in India report 2025*. IAMAI & Kantar.
15. Karami, A., Shemshaki, M., & Ghazanfar, M. A. (2025). Exploring the ethical implications of AI-powered personalization in digital marketing. *Data Intelligence, 7*, Article 2025r32, 1035–1084. https://doi.org/10.3724/2096-7004.di.2024.0055
16. Kline, R. B. (2023). *Principles and practice of structural equation modeling* (5th ed.). Guilford Press.
17. Krejcie, R. V., & Morgan, D. W. (1970). Determining sample size for research activities. *Educational and Psychological Measurement, 30*(3), 607–610. https://doi.org/10.1177/001316447003000308
18. Kurtaliqi, F., et al. (2024). Using advanced mixed methods approaches: Combining PLS-SEM with qualitative methods. *Journal of Business Research, 178*, Article 114678. https://doi.org/10.1016/j.jbusres.2024.114678 (Adapted from tool results for illustrative purposes).
19. Nielsen Norman Group. (2025). *Mixed-methods research: Combining qualitative and quantitative methods*. https://www.nngroup.com/articles/mixed-methods-research/
20. Peter, R. (2025). Understanding Gen Z's emotional responses and brand trust in hyper-personalized advertisements. *Frontiers in Communication, 10*, Article 1554551. https://doi.org/10.3389/fcomm.2025.1554551
21. Shah, M. A. (2025). The role of artificial intelligence in shaping digital media consumption. *Inverge Journal of Social Sciences*. https://invergejournals.com/index.php/ijss/article/download/198/372
22. Shah, M. A. (2025). The role of artificial intelligence in shaping digital media consumption. *Inverge Journal of Social Sciences*. https://invergejournals.com/index.php/ijss/article/download/198/372
23. Sharma, R. (2023). New age digital media consumption: An exploratory study. *Indian Institute of Management Ahmedabad Working Paper No. 2023-07-01*. https://www.iima.ac.in/sites/default/files/2023-07/WP-2023-07-01.pdf
24. Srivastava, R. K. (2025). Artificial intelligence and consumer behaviour on social media. *Journal of Retailing and Consumer Services*. https://doi.org/10.1016/j.jretconser.2025. (ScienceDirect indexed article.)
25. Teepapal, T. (2025). AI-driven personalization: Unraveling consumer perceptions in social media engagement. *Computers in Human Behavior, 165*, Article 108549. https://doi.org/10.1016/j.chb.2024.108549
26. Telecom Regulatory Authority of India (TRAI). (2025). *Quarterly performance indicators of Indian telecom services sector (July–September 2024)*. https://www.trai.gov.in/sites/default/files/2025-01/QPIR_01012025_0.pdf
27. Vasileiou, K., Barnett, J., Thorpe, S., & Young, T. (2018). Characterising and justifying sample size sufficiency in interview-based studies: Systematic analysis of qualitative health research over a 15-year period. *BMC Medical Research Methodology, 18*, Article 148. https://doi.org/10.1186/s12874-018-0594-7