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Perceived Algorithmic Personalisation and Platform Trust Among Generation Z in India: The Role of Cultural Congruence

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Abstract

This study examines how algorithmic personalisation relates to platform trust among Generation Z users in India. It proposes cultural congruence, the perceived fit between recommendations and a user's cultural identity, as a construct that may link personalisation to trust, tests whether it also conditions that link, and models a parallel privacy pathway. Survey data from 302 platform users were analysed with covariance-based structural equation modelling and moderated regression. Perceived personalisation was positively associated with cultural congruence ($\beta = 0.459$) and privacy concern ($\beta = 0.238$). Cultural congruence was positively associated with trust in platforms' data practices ($\beta = 0.280$), and the indirect effect of personalisation on trust through cultural congruence was significant ($\beta = 0.129$), whereas the bootstrapped direct effect was not significant. The test of cultural congruence as a moderator of the personalisation–trust association was inconclusive ($B = 0.169$, $p = 0.249$ with HC3 standard errors). Privacy concern was positively associated with algorithmic resistance ($\beta = 0.427$) but not with trust; unexpectedly, resistance was positively associated with trust ($\beta = 0.239$). The findings are consistent with the possibility that, for this cohort, personalisation is associated with trust largely to the extent that recommendations are experienced as culturally fitting. As a suggestion for policy discussion, limited to young users who are in or have completed higher education, we note that India's Digital Personal Data Protection Act 2023 regulates consent but not the cultural representativeness of recommendation outputs.

Keywords: algorithmic personalisation; cultural congruence; platform trust; algorithmic resistance; privacy concern; Generation Z; India; CB-SEM; mediation; DPDPA 2023

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1. Introduction

Algorithmic personalisation has become the main commercial mechanism through which digital platforms build engagement, loyalty and revenue [1,2]. Netflix, Instagram, YouTube and Amazon all use recommendation systems that adjust content, products and advertising for each user, drawing on behavioural data that are updated all the time. Generation Z, usually defined as people born between 1997 and 2012 [3], is the first cohort to have grown up with such systems, and for these users personalisation shapes identity, trust and cultural experience as well as consumption. Behind this commercial success lies a structural problem. Many widely used recommendation and language systems are built on data that reflect Western digital behaviour and Western cultural defaults [4,5]. Where markets

are culturally diverse, the recommendations that result are often technically accurate yet culturally out of place. They follow a user's click history but miss his or her cultural frame of reference. Younas and Zeng [6] describe this as the "Cultural Cognition Gap". In their account, artificial intelligence (AI) reasons from static patterns, whereas human cognition adapts to culture, and the distance between the two becomes visible when systems fail in real-world deployment.

This matters because trust depends on more than technical accuracy. In collectivist societies, users judge what a platform shows them partly by what it means for their cultural community, and not only by whether it suits them as individuals. Westjohn et al. [7], drawing on more than 6000 respondents in 36 countries, found that collectivism increases trust propensity through social projection. Hassan et al. [1] show that personalised recommendations strengthen the trust–satisfaction–loyalty cycle, but the conditions under which personalisation produces this trust-building effect remain unclear. A parallel literature documents the privacy paradox, in which users express concern about data collection yet continue to use personalised platforms [8–12]. This work suggests that trust and concern may operate through partly separate pathways, although the evidence is mixed.

Three research gaps motivate this study. First, few studies have examined cultural congruence as a pathway to, or a condition on, personalisation-driven trust, and we know of none in an emerging-market Generation Z sample; studies of the personalisation–trust relationship [1,13] have not treated cultural alignment as either a mediator or a boundary condition. Second, the cultural recognition pathway and the privacy concern pathway have not been modelled together within a single covariance-based structural equation modelling (CB-SEM) framework for this population, so their relative associations with trust have not been compared directly. Third, the resistance–trust form of the privacy paradox, in which privacy concern prompts protective behaviour without reducing platform trust, has received little empirical attention in developing markets. Two research questions follow. RQ1: Is perceived algorithmic personalisation associated with platform trust through, and conditional on, cultural congruence? RQ2: Is a privacy pathway, running from personalisation to privacy concern and algorithmic resistance, also associated with trust? The privacy path is included as a contrast to the cultural path: privacy calculus theory (Section 2.5) predicts that personalisation raises concern about how personal data are used, so modelling both paths shows whether personalisation is linked to trust through cultural fit, through data concerns, or through both. Results on the privacy path that ran against expectation are treated as exploratory. The model has two pathways from perceived algorithmic personalisation (APP). One is cultural: APP is linked to cultural congruence (CC), and CC to trust in platform (TR). The other runs through privacy: APP is linked to privacy concern (PC), and PC to algorithmic resistance (AR). We test it with CB-SEM, which Dash and Paul [14] recommend for confirmatory theory testing. CC is also expected to moderate the association between APP and TR. Survey data from 302 Indian Generation Z platform users are analysed. The results show that personalisation is associated with trust mainly through cultural congruence, although the cross-sectional design cannot establish mediation, and the test of cultural congruence as a boundary condition was inconclusive. They also show that privacy concern is linked to resistance but not to trust, and that resistance is, unexpectedly, positively associated with trust. We also suggest possible governance implications for India's Digital Personal Data Protection Act (DPDPA) 2023 [15]. Section 2 reviews the literature and develops the hypotheses, Section 3 describes the method, Section 4 reports the results, Section 5 discusses them and Section 6 concludes.

2. Literature Review and Hypothesis Development

2.1. Generation Z, Trust and Algorithmic Platforms

Young people's trust in brands and institutions has been declining. In a survey of 1534 people aged 15–24 in Finland and the United Kingdom, respondents trusted organisations' social media content more when they saw those organisations as listening [16]. Comparisons across generations show a similar pattern, with younger consumers relying more on peer reviews and user-generated content than on company messages when deciding what to believe [17]. For this cohort, trust seems to be conditional. It has to be earned, often through signals that young users take to come from people like themselves.

Trust also matters for behaviour. In a study of 754 Generation Z users of short-form video platforms in China, about 31% of the effect of AI recommendations on spontaneous buying intention ran through perceived trust [18]. Evidence from Mexico shows perceived AI accuracy and attitudes toward AI raising brand trust, which in turn predicted purchasing [19]. In another study, of 1128 Generation Z respondents, familiarity with AI influenced purchase intention through perceived usefulness [20]. In India, Lyngdoh et al. [21] found that socially isolated and anxious Generation Z users were more willing to share personal information, especially when they saw a firm's privacy policy as transparent. What none of these studies asks is whether the cultural content of recommendations matters for trust. That is the question we address.

2.2. Perceived Algorithmic Personalisation

By perceived algorithmic personalisation (APP) we mean a user's subjective judgement that a platform's recommendation system accurately reflects his or her preferences, needs and identity [22]. As measured here, APP covers the perceived fit of recommendations and suggestions to the user's interests and needs (APP1, APP2, APP5) and their perceived usefulness for discovery (APP3, APP4); it is a perception of personalisation, not a direct measure of recommendation accuracy. Evidence for its downstream effects comes from several settings. In one of the earliest studies, Komiak and Benbasat [23] found that perceived personalisation raised both cognitive and emotional trust in recommendation agents. In a study of 754 Generation Z users of short-form video platforms, Hu et al. [18] found that AI-powered personalised recommendations increased spontaneous buying intention through two mediators, perceived usefulness (35.17%) and perceived trust (31.18%), which together accounted for 66.35% of the total effect. Hassan et al. [1] showed that tailored recommendations strengthen the links between trust, satisfaction and loyalty in e-commerce. Extending the unified theory of acceptance and use of technology (UTAUT2) to mobile news apps in India, Cheng et al. [24] found that personalisation substantially increased continuous-use intention, which indicates that personalisation perceptions matter in the Indian digital market.

Personalisation also shapes Generation Z behaviour more directly. Singh [25], extending the technology acceptance model (TAM), found that perceived risk, usefulness, ease of use, privacy, security, customer trust and trust toward sellers shape Generation Z online buying intentions. Applying a modified TAM to 384 Generation Z consumers, Shiddieqy and Widarmanti [26] found that AI-driven personalisation, including ad personalisation, chatbots and AI-based recommendations, had a significant positive effect on purchase decisions, with trust in AI as a significant mediator. Peter et al. [27] examined Generation Z's emotional responses and brand experiences with hyper-personalised advertising driven by generative AI. What this evidence does not show is how personalisation interacts with cultural identity to shape trust. In collectivist markets, where individual identity is shaped to a large extent by cultural group membership [28], personalisation accuracy and cultural recognition are hard to separate in

experience. An algorithm that correctly learns an Indian user's preferences is likely also to learn the community preferences that make up a large part of those preferences. This reasoning underlies the first hypothesis.

H1. *Perceived algorithmic personalisation is positively associated with cultural congruence.*

2.3. Cultural Congruence

Cultural congruence (CC) refers to the perceived alignment between platform content and the user's cultural values, norms and identity [29]. Self-congruity theory predicts that consumers respond more favourably to offerings that match their self-concept [30]. Mehmood et al. [5], analysing 487 critical incidents reported by 176 consumers in Belgium and Pakistan, show that AI-enabled personalisation can both extend and restrict the self, and that these effects differ by cultural context. Michel et al. [31] found that alignment between brand values and consumers' own value priorities drives positive brand responses through self-expansion. Westjohn et al. [7], across four studies, showed that collectivism shapes trust propensity through social projection, a mechanism through which cultural alignment in platform outputs may translate into trust. Xu and Chen [32] ran two 2 × 2 experiments. Recommendation fit and choice visibility increased perceived control, perceived control raised satisfaction with the recommendations, and satisfaction in turn raised platform trust. Cultural congruence can be seen as one form of such fit, and possibly an especially important one in a collectivist market.

In digital platform contexts, Picoto and Pinto [33], using a multi-method approach with data from four countries, showed that Hofstede's cultural dimensions moderate the relationship between intention and use for mobile banking. In collectivist markets, cultural congruence may decide whether a platform feels relevant in the first place. It is therefore more than just one aspect of content quality. Its distinctiveness from perceived cultural identity threat (PCIT) was examined in the confirmatory factor analysis (CFA); PCIT was dropped because of cross-loadings, as explained in Section 3.2.

Work on algorithmic identity reaches a similar conclusion. For Lury and Day [34], personalisation is a mode of individuation that sorts people into ever finer categories. Kant [35] shows that users live with the identities personalisation assigns them, and sometimes push back against them. TikTok users speak of their feed as an "algorithmic crystal" that shows them parts of themselves and connects them to wider groups [36]. Users also adapt recommendations to their local routines. In Costa Rica, Netflix viewers "domesticate" the algorithm as much as it shapes them [37]; viewers in the Arab world report a similar negotiation between a global catalogue and local meaning [38]. How people judge algorithms in the first place also depends on culture. Users in the United States and the United Arab Emirates perceived algorithmic news differently depending on their cultural value orientations [39], and the cues that made a recommender system seem trustworthy varied between countries [40]. Research on Netflix describes a recommender that both builds and narrows cultural taste [41,42], and diversity claims that coexist with a system still centred on majority audiences [43]. Across these studies, users notice whether content fits their culture, and they react to it.

We also expect cultural congruence to be directly associated with trust. The reason can be seen through the ability–benevolence–integrity (ABI) model of trustworthiness [44,45]. When a feed reflects a user's cultural world, it signals ability, since the system appears to understand the user. It also signals benevolence, as the platform seems to take the user's community seriously rather than push a generic global catalogue. Integrity is involved too, because cultural norms partly define what counts as acceptable content. Value-congruity and social-projection accounts both predict that

people extend more trust to parties that appear to share their values [7,31], and Whitwam [46] examines how social commerce platforms transform trust-building among Generation Z consumers in different cultures. Because the trust measure used here concerns platforms' honesty, handling of personal data and general goodwill towards users (Section 2.6), H2 tests whether cultural congruence is associated with this form of trust, not with trust in the recommendations themselves. The second hypothesis concerns the direct path from cultural congruence to trust.

H2. *Cultural congruence is positively associated with trust in platform.*

2.4. Privacy Concern

Privacy concern (PC) reflects an individual's anxiety about how digital platforms collect, store, use and potentially misuse personal data [47]. The Internet Users' Information Privacy Concerns (IUIPC) scale [47], which covers collection, control and awareness, remains the field standard, and Gross [48] supports its validity in a recent psychometric re-evaluation comparing the IUIPC-10 and IUIPC-8 versions. Privacy calculus theory [49] treats the decision to disclose information as a trade-off, with the benefits of personalisation on one side and the risks of data exposure on the other. Dinev and Hart [49] tested this with structural equation modelling (SEM) on 369 respondents and found that trust and personal interest can outweigh perceived privacy risk, although the result depends on how each person weighs the two.

Among Generation Z users, privacy concern is strong but takes paradoxical forms. In an SEM study of 414 Generation Z consumers, McKee et al. [12] found that a privacy–benefits paradox and an avoidance–annoyance paradox both had strong effects on intentions to avoid brands that fail to personalise their marketing. Ameen et al. [50] explored the same tension between personalisation and privacy in how consumers interact with smart technologies in shopping malls. Cloarec et al. [10] found that, on social media, disclosure for personalisation runs through happiness with the internet and posting frequency, with trust beliefs and information-collection concerns moderating these effects, which suggests that personalisation and concern are only partly related. In a sequential multi-study design with Indian Generation Z, Lyngdoh et al. [21] found that social isolation and social anxiety increased willingness to share personal information on social media, and that this effect was stronger when the firm's privacy policy was perceived as transparent and ethical. In connected-device services, Kim et al. [51] found that people paid limited attention to perceived privacy risk when providing information for a more personalised service, except in health care, where risk was high. Aguirre et al. [52] showed that personalised advertising can backfire when data collection is covert, and Tucker [53] found that giving users more control over privacy settings made them more responsive to personalised ads. Awad and Krishnan [13] showed that consumers who value information transparency are less willing to be profiled for personalisation. Whether ordinary personalisation quality raises privacy concern is still an open question.

H3. *Perceived algorithmic personalisation is positively associated with privacy concern.*

2.5. Algorithmic Resistance

Algorithmic resistance (AR) covers the active and passive ways users limit, circumvent or disrupt recommendation algorithms [54]. It includes changing privacy settings, giving false information, using ad blockers or private browsing, avoiding recommended content and deliberately sharing less data. Privacy calculus theory [49] predicts that higher concern prompts protective action through heightened risk perception. In the present study, however,

three of the four retained items (AR2, AR3, AR5) describe privacy-protective behaviours, and only AR4 refers directly to recommendations. The construct as measured is therefore closer to privacy-protective resistance than to resistance to recommendation algorithms in general, and the results for H5 and H7 should be read in this light.

McKee et al. [12] used privacy calculus theory to examine why Generation Z consumers adopt ad blockers, private browsers and other anti-tracking measures, and linked personalisation–privacy tensions to brand avoidance. Reactance to personalisation is also a documented driver of ad blocking [55]. Xie et al. [56] showed that users' motivations for using short-video platforms shape their resistance to algorithms. Zhang et al. [57] showed that homogeneous information flows in recommender systems prompt coping responses in the form of algorithmic resistance and avoidance. Cheng and Peng [58], using SEM on 506 questionnaires, found that algorithmic transparency and perceived manipulation shape algorithmic avoidance, with perceived manipulation mediating the effects of information quality and homogeneous recommendations. Ma et al. [59] showed that narrow and repetitive recommendations on short-video platforms lead to exhaustion, psychological reactance and intentions to discontinue use. The link from concern to resistance is well supported. Less clear is whether cultural alignment in recommendation outputs reduces resistance, that is, whether resistance is driven by concerns about data collection, which cultural alignment cannot address, or by dissatisfaction with outputs, which it can.

H4. *Privacy concern is positively associated with algorithmic resistance.*

H5. *Cultural congruence is negatively associated with algorithmic resistance.*

2.6. Trust in Platform

Trust in platform (TR) refers to users' confidence that the platform is honest, uses personal data as promised, is competent in protecting user information and generally acts in their interests. As operationalised (Appendix A), the TR items refer to "websites I use" in general, and respondents were asked to answer on the basis of their experiences with platforms such as Instagram, Netflix, Amazon, Spotify and YouTube rather than one platform. TR therefore measures general trust in the data practices of the platforms a respondent uses, not trust in a specific platform or in its recommendations, and the conclusions drawn from it are limited accordingly. Because privacy concern also refers to data handling, the PC–TR association (H6) links two data-related perceptions. We follow the definition of trust as a willingness to accept vulnerability based on positive expectations of another party's behaviour [60], and the ability–benevolence–integrity model of Mayer et al. [44], which remains the dominant framework [45]. Recent studies apply this thinking to algorithmic platforms. Singh [25] found that customer trust and trust toward sellers shape Generation Z online buying intentions. Teepapal [61] found that AI-driven personalisation on social media increases trust and perceived usefulness, while privacy concerns do not affect engagement. Algorithmic failure can also erode trust: Ma et al. [59] showed that greedy recommendation features on short-video platforms produce exhaustion and intentions to discontinue use.

Research on the privacy paradox makes the prediction that concern lowers trust less straightforward. Early work found that stated concern did not predict actual disclosure [8,62], and a major review concluded that gaps between privacy attitudes and behaviour are common but context-dependent [9]. In a three-wave panel of a representative German sample, Dienlin et al. [11] found that people who were more concerned about privacy shared slightly less information. They found no long-term effects of concern on sharing, though, so the evidence argues against a strong paradox while showing that the

effects are small. Cloarec et al. [10] show that trust beliefs and collection concerns jointly shape disclosure on social media. Colnago et al. [63] documented a reverse privacy paradox, in which people who dismiss privacy concerns nonetheless adopt protective behaviours. Bright et al. [64] examined how privacy concerns affect social media engagement among US consumers. Knowles and Conchie [65] proposed hopeful trust, in which people keep trusting a service they are uneasy about, as one explanation for continued use. Since the evidence is mixed, we keep the usual directional predictions of privacy calculus theory and treat the paradox as the rival account.

H6. *Privacy concern is negatively associated with trust in platform.*

H7. *Algorithmic resistance is negatively associated with trust in platform.*

2.7. Cultural Congruence as a Moderator of the Personalisation–Trust Relationship

The final hypothesis asks whether cultural congruence also conditions the personalisation–trust relationship. Personalisation–trust research has tended to treat accuracy as the main driver of trust [1,13]. Accuracy is necessary but may not be sufficient: in collectivist markets, individual and cultural identity are closely intertwined [7,28], so an algorithm that achieves accuracy without cultural accommodation offers only partial recognition of the user. Luna and Gupta [29] treat cultural congruence as a quality dimension of cross-cultural consumer communication that is distinct from technical accuracy. Mehmood et al. [5] show that the effect of AI personalisation on self-concept differs by cultural context, and Whitwam [46] examines how social commerce platforms are reshaping trust-building among Generation Z consumers across cultures.

Picoto and Pinto [33] show that cultural dimensions moderate the relationship between intention and use across countries, and Michel et al. [31] show that value congruity between brand and consumer drives positive responses through self-expansion. From the ABI perspective [44], accuracy alone mainly signals the platform's ability; when accurate recommendations are also culturally fitting, the same accuracy is more likely to be read as understanding and goodwill. We expect that personalisation should be more strongly associated with trust when it is perceived as culturally aligned.

H8. *Cultural congruence positively moderates the relationship between perceived algorithmic personalisation and trust in platform, such that the association is stronger at higher levels of cultural congruence.*

Taken together, H1 and H2 also imply an indirect pathway from personalisation to trust through cultural congruence. Rather than stating it as a separate hypothesis, we examine it as part of RQ1, alongside the moderation test in H8. Figure 1 summarises the proposed model.

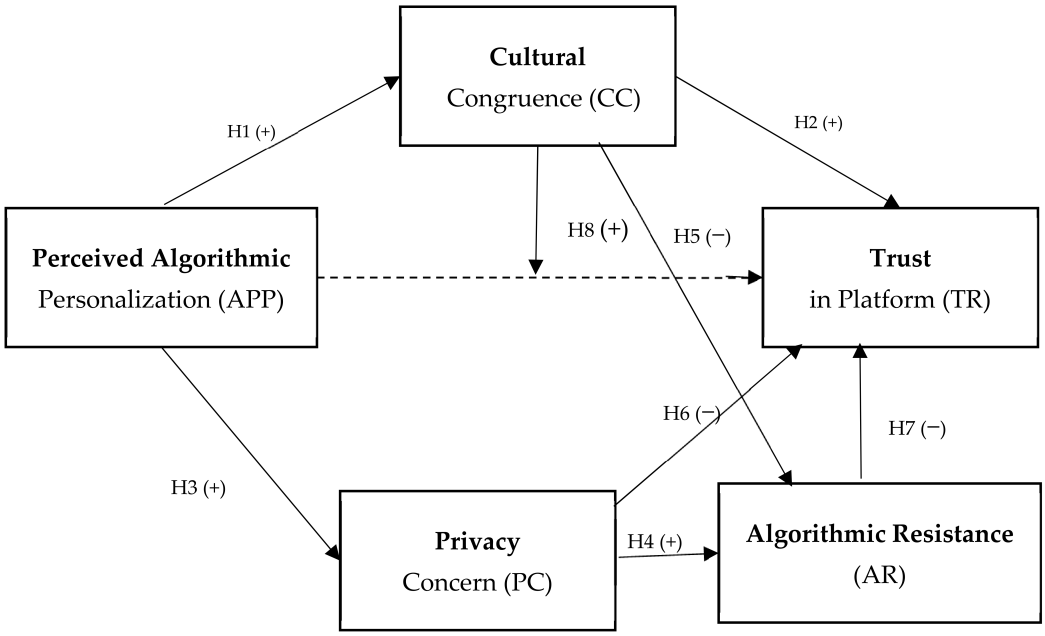


Figure 1. Proposed conceptual model. Solid arrows show the hypothesised paths (H1–H7). H8 proposes that cultural congruence moderates the association between perceived algorithmic personalisation and trust in platform (dashed line).

3. Materials and Methods

3.1. Research Design and Justification

A quantitative cross-sectional survey design was used. Following Dash and Paul [14], who show that CB-SEM is preferable to PLS-SEM for confirmatory theory testing, the measurement and structural models were estimated by maximum likelihood in IBM AMOS 26, following Anderson and Gerbing's [66] two-step procedure: the measurement model was evaluated first, and the structural paths were then tested. Indirect effects (RQ1 and RQ2) were tested with 5000 bias-corrected bootstrap resamples. Because the model contains several mediators, specific indirect effects were assessed with Monte Carlo confidence intervals [67]. AMOS does not readily test interactions between latent variables, so the moderation hypothesis (H8) was tested on mean-centred composite scores [68] with PROCESS v5.0 (Model 1) [69], using HC3 heteroskedasticity-consistent standard errors and controlling for gender, age, education and region.

Common method bias was assessed in two ways. In Harman's [70] single-factor test, the first unrotated component explained 24.8% of the variance in the 23 retained items, so no single factor accounted for the majority of the variance. Because this test is a weak screen on its own [71], we also applied Lindell and Whitney's [72] marker-variable correction, using the smallest positive correlation between construct scores ($r = 0.067$, between CC and AR) as a conservative estimate of method variance. The APP–CC, CC–TR, PC–AR, APP–TR and AR–TR correlations remained significant after adjustment (adjusted $r = 0.337$, 0.269, 0.324, 0.232 and 0.163; all $p < 0.01$). Procedurally, predictor and outcome items were placed in separate sections of the questionnaire, and respondents were told that their responses would be treated confidentially. Common method variance is therefore unlikely to explain the main associations, although it cannot be ruled out.

3.2. Survey Instrument and PCIT Exclusion

The survey measured six constructs on five-point Likert scales (1 = strongly disagree; 5 = strongly agree): perceived algorithmic personalisation [22], cultural congruence [29], privacy concern [47], algorithmic resistance [12], trust in platform [44] and perceived

cultural identity threat (PCIT) [73]. Section 3.4 gives the sources of the items. Following social identity theory [73], we first included PCIT in the structural model as an outcome of cultural congruence (CC → PCIT). The aim was to test whether platform content that seems culturally misaligned provokes a separate identity-threat response. In the CFA, PCIT did not separate from CC: its heterotrait–monotrait ratio with CC was 0.87, above the 0.85 criterion [74], and three PCIT items ("Western digital platforms often overlook Indian cultural values", "Global platforms promote Western lifestyles that do not align with our traditions" and "The growing influence of Western apps weakens our cultural identity") shared substantial variance with the CC items. The CC item "Many Western apps fail to represent local cultural values" (CC5) loaded with the PCIT items was removed. The CC → PCIT path was non-significant ($\beta = 0.165$, $p = 0.179$), and PCIT explained little variance ($R^2 = 0.027$). PCIT was removed before the hypotheses were tested. We treat this as a measurement limitation rather than a substantive finding: the present items were not distinct enough to separate perceived cultural incongruence from perceived cultural identity threat in this sample, which does not imply that the two constructs are identical. Future research should examine the distinction with separately developed and piloted scales. Item AR1 was also removed during the CFA. The final model comprises five constructs and 23 items.

3.3. Sample

The study targeted Generation Z digital platform users aged 18–29. This cohort is the first to have grown up entirely with digital platforms, and its trust formation, privacy attitudes and responses to algorithmic personalisation differ from those of older cohorts [12,25,75]. In India it is also among the largest and fastest-growing user groups for over-the-top (OTT) streaming, social media and e-commerce [76]. For the questions we ask, it therefore matters both commercially and for policy.

We planned a quota sample based on geographic region. Quota sampling suits situations where there is no complete sampling frame but known segments of the population can still be covered in a structured way. No government register, platform subscriber database or institutional list identifies Indian Generation Z platform users as a population, so probability sampling was not feasible. Regional quotas covered five geographically and linguistically distinct zones (North, South, West, Central and East), because India's platform users differ considerably in language, cultural practice and exposure to algorithmic content across regions. A sample from a single city or state would have reflected one regional context only. Regional quotas were monitored during data collection but were not fully achieved: respondents from North (43.0%) and South India (30.8%) make up most of the sample, whereas Central (4.6%) and East India (5.3%) are under-represented (Table 1). As a benchmark, Census 2011 population shares by the zonal-council grouping of states are 38.6% for North and Central India combined (North and Central are combined because respondents classified their own region without definitions, and Uttar Pradesh and Uttarakhand, which form the Central zonal council with Madhya Pradesh and Chhattisgarh, are commonly regarded as North India), 20.9% for South, 14.4% for West, 22.3% for East and 3.8% for the North-East [77]; the corresponding sample shares are 47.6%, 30.8%, 14.6%, 5.3% and 0% (the questionnaire offered no North-East option). The sample therefore over-represents North, Central and South India and under-represents East and North-East India. We could not locate official zone-level figures for Generation Z or for internet users, so these comparisons are limited to the total population. Because the questionnaire was distributed mainly through academic networks and most respondents were enrolled in or had completed higher education, total population shares are only a rough reference point, and the regional distribution probably also reflects where these networks reached.

Table 1. Sample demographic profile ($N = 302$).

Variable	Category	*n*	%
Gender	Female	165	54.6
	Male	137	45.4
Age (years)	18–20	83	27.5
	21–23	98	32.5
	24–26	118	39.1
	27–29	3	1.0
Education	Undergraduate	118	39.1
	Graduate	20	6.6
	Postgraduate	164	54.3
Region	North India	130	43.0
	South India	93	30.8
	West India	44	14.6
	East India	16	5.3
	Central India	14	4.6
	India (region not specified)	5	1.7
Daily internet use	Less than 1 h	6	2.0
	1–3 h	85	28.1
	3–5 h	82	27.2
	5–7 h	72	23.8
	More than 7 h	57	18.9

Note: Percentages may not sum to 100 because of rounding. The education question offered the options Undergraduate, Graduate, Postgraduate, Doctorate and Other, with no definitions, and no respondent chose Doctorate or Other. Respondents gave the highest level they were studying for or had completed. Undergraduate means a student enrolled in a bachelor's programme, Graduate means a holder of a bachelor's degree, and Postgraduate means a student enrolled in, or a holder of, a master's degree. The region question read "Region you belong to".

Because the design is non-probability, statistical generalisation to all Indian Generation Z platform users is not claimed. Instead, the findings are presented as analytical generalisations [78], that is, as evidence that the proposed mechanisms work as hypothesised within this sample. The sample ($N = 302$) is larger than the power analysis required, and wherever published instruments existed, the constructs were measured with scales adapted from them [12,22,44,47]. Claims about whole populations would need replication in other collectivist digital markets, such as Indonesia, Nigeria, Brazil and Vietnam.

Three filter questions at the start of the survey, placed before any construct items, confirmed eligibility. Anyone who did not meet a criterion was taken to a disqualification screen.

Filter 1: "How old are you?" Only respondents aged 18–29 could continue.

Filter 2: "Do you actively use at least one of the following platforms (Instagram, YouTube, Amazon, Netflix or Spotify) for at least one hour per day?" Only respondents who answered yes could continue. We named specific platforms rather than asking one general usage question, because this measures actual engagement with algorithmic recommendation systems more precisely. Even so, six respondents (2.0%) reported less than one hour of total daily internet use in the demographic section (Table 1). Respondents may have understood "internet use" differently, for example as not including app-based streaming. Because there were so few such cases, we kept them. Filter 2 established that respondents used at least one of these platforms, but it did not record which. Platform composition therefore could not be reported or tested as a moderator, and the results describe users' general experiences across these platforms (Section 5.5).

Filter 3: "Are you currently residing in India?" Those who did not meet this criterion were sent to the disqualification page. This kind of screening is common in consumer

research in emerging markets, where no population-wide sampling frame exists [79]. We collected the data with a structured online questionnaire in Google Forms, which was shared through academic networks, social media channels and professional contacts. Regional quotas were tracked during data collection, and Table 1 reports the distribution that was achieved. Taking part was voluntary. Respondents were informed of the study's academic purpose, told that their responses would be treated confidentially, and told that they could withdraw at any time without consequence.

After submission, three quality controls were applied. An attention-check item asked respondents to choose a specified response option; responses completed in under 180 s were removed as implausibly fast; and questionnaires with less than 90% of items completed were removed as incomplete [71]. Screening and these checks excluded 20 of the 322 initial responses, which left an analytical sample of $N = 302$. According to a sensitivity analysis in G*Power 3.1 [80] ($f^2 = 0.15$, $\alpha = 0.05$, ten predictors as in the moderation model), 118 respondents were needed for 80% power, and with $N = 302$ the power for an effect of this size was above 0.99. Because the effect of interest for H8 is the interaction term, power was also computed for a small interaction effect ($f^2 = 0.02$, $\alpha = 0.05$, one tested predictor among ten): with $N = 302$ it was about 0.69, so the moderation test was underpowered for small effects. Table 1 shows the demographic profile of the final sample.

Although the eligibility range was 18–29 years, only three respondents (1.0%) were aged 27–29. All three were retained: respondents aged 27–29 at the time of data collection (2026) were born between 1996 and 1999 and so fall at, or very close to, the start of Generation Z as defined by Dimock (1997–2012) [3]; because age was recorded in bands, exact birth years are not available. Re-estimating the structural model without these three respondents ($N = 299$) left the fit (CFI = 0.969, TLI = 0.964, RMSEA = 0.037), every hypothesis decision, and the indirect effect of APP on TR through CC ($\beta = 0.133$; unstandardised 95% Monte Carlo CI [0.063, 0.252]) essentially unchanged, and the APP × CC interaction remained non-significant ($B = 0.173$, $p = 0.235$). Most respondents were postgraduates (54.3%), and most were women (54.6%). The large share of postgraduates is probably a result of distributing the survey through academic networks. We compared postgraduates ($n = 164$) with undergraduates and graduates combined ($n = 138$) in a multi-group analysis. Neither the measurement weights ($\Delta\chi^2(18) = 17.61$, $p = 0.482$) nor the structural weights ($\Delta\chi^2(8) = 6.74$, $p = 0.565$) differed, so education did not change the structural paths.

3.4. Measures

Every construct was measured on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree), and Appendix A gives the full wording of every item administered, including the items removed during the CFA, with standardised loadings for the retained items. We adapted the APP scale (5 items, $\alpha = 0.854$) from Shin [22]. CC (4 items, $\alpha = 0.801$) was developed for this study from the cultural congruence framework of Luna and Gupta [29]. We designed the wording of items for this study based on Luna and Gupta's framework. Their wording was refined in discussion among the authors and then checked by the doctoral research advisory committee and the research team at the authors' institution. No cognitive interviews or separate pilot test were conducted. CC4 ("I prefer digital platforms that are sensitive to my cultural background") expresses a preference rather than perceived fit, which is acknowledged as a limitation (Section 5.5). Re-estimating the model without CC4 slightly improved fit (CFI = 0.974, TLI = 0.970, RMSEA = 0.035) and left all hypothesis decisions unchanged; the three-item CC scale had CR = 0.786 and AVE = 0.551, and the indirect effect of APP on TR through CC remained significant ($\beta = 0.121$; unstandardised 95% Monte Carlo CI [0.051, 0.231]). Respondents were instructed to answer on the basis of their personal experiences with online platforms such as Instagram, Netflix, Amazon,

Spotify and YouTube, and the items were presented in a fixed order, in a separate section for each construct. Each section had a title naming the construct and a one-sentence description (for CC: "Measures the extent to which personalised content aligns with users' cultural values"). These labelled sections indicated what each block of items referred to, but item order was not randomised and the labels may have increased response consistency within blocks (Section 5.5). APP and CC were empirically distinct: their HTMT ratio was 0.462, and the square roots of their AVEs (0.735 and 0.714) exceeded their latent correlation (0.455) (Section 4.1). (Table 3). A model in which the APP and CC items loaded on a single factor fitted the data substantially worse than the measurement model with separate factors ($\chi^2(223) = 577.50$, CFI = 0.879, TLI = 0.862, RMSEA = 0.073, compared with $\chi^2(219) = 309.34$, CFI = 0.969, TLI = 0.964, RMSEA = 0.037; $\Delta\chi^2(4) = 268.16$, $p < 0.001$). PC (5 items, $\alpha = 0.868$) was adapted from the IUIPC scale of Malhotra et al. [47], whose validity has been re-examined by Gross [48]. AR (4 items, $\alpha = 0.794$) was adapted from McKee et al. [12] and Airoldi and Rokka [54]. TR (5 items, $\alpha = 0.877$) operationalised the ABI framework of Mayer et al. [44], consistent with Schoorman et al. [45]. Its items refer to "websites I use" in general and to their handling of personal data, so TR measures general trust in the data practices of the platforms a respondent uses rather than trust in one platform or in its recommendations (Section 2.6). PCIT was measured but removed after the CFA, as described in Section 3.2. Composite scores for the moderation analysis were computed as item means.

4. Results

4.1. Measurement Model

Measurement adequacy was judged against conventional criteria: Cronbach's alpha and composite reliability (CR) above 0.70, standardised loadings above 0.50, and average variance extracted (AVE) above 0.50, or above 0.40 when CR exceeds 0.60 [81,82]. Discriminant validity was assessed with the heterotrait–monotrait ratio (HTMT, below 0.85) [74] and the Fornell–Larcker criterion [82]. Model fit was evaluated against the normed chi-square (χ^2/df) below 3 [81], the root mean square error of approximation (RMSEA) of 0.06 or less [83], with values up to 0.08 regarded as reasonable [84], and the comparative fit index (CFI) and Tucker–Lewis index (TLI) of 0.95 or more [83,85].

The five-factor measurement model fitted the data well: $\chi^2(219) = 309.34$, $p < 0.001$, χ^2/df = 1.41, CFI = 0.969, TLI = 0.964, incremental fit index (IFI) = 0.969, RMSEA = 0.037 (90% CI [0.027, 0.046], p of close fit (PCLOSE) = 0.991), goodness-of-fit index (GFI) = 0.919 and root mean square residual (RMR) = 0.028. The adjusted goodness-of-fit index (AGFI = 0.898) was marginally below 0.90. The error terms of PC4 and PC5 were allowed to covary on the basis of the modification indices and because both items refer to tracking-based personalisation ("I am uncomfortable with apps tracking my online behavior"; "I believe that personalization often invades my online privacy") (r = 0.24, $p = 0.001$).

Table 2 reports reliability and convergent validity. Cronbach's alpha ranged from 0.794 to 0.877 and CR from 0.795 to 0.878. All standardised loadings were significant ($p < 0.001$) and ranged from 0.624 to 0.841. AVE exceeded 0.50 for APP (0.540), CC (0.510), PC (0.566) and TR (0.591). For AR it was marginally lower (0.493), but CR exceeded 0.60 and the square root of AVE exceeded AR's correlations with every other construct, so convergent validity was considered adequate [82]. Discriminant validity was supported (Tables 3 and 4): the square root of each construct's AVE exceeded its correlations with the other constructs, maximum shared variance (MSV) was below AVE for every construct, and all HTMT ratios were below 0.85 (range 0.09–0.46) [74,82]. The strongest latent correlation was between APP and CC (r = 0.455), consistent with the view that personalisation and cultural fit are closely linked in users' experience.

Table 2. Measurement model: reliability and convergent validity ($N = 302$).

Construct	Items	α	CR	AVE	MSV	Loadings
Perceived algorithmic personalisation (APP)	5	0.854	0.854	0.540	0.207	0.713–0.753
Cultural congruence (CC)	4	0.801	0.805	0.510	0.207	0.624–0.775
Privacy concern (PC)	5	0.868	0.854	0.566	0.183	0.674–0.841
Algorithmic resistance (AR)	4	0.794	0.795	0.493	0.183	0.678–0.735
Trust in platform (TR)	5	0.877	0.878	0.591	0.135	0.739–0.816

Note: α = Cronbach's alpha (SPSS); CR = composite reliability; AVE = average variance extracted; MSV = maximum shared variance. Loadings are standardised CFA loadings, all $p < 0.001$. CR for PC accounts for the PC4–PC5 error covariance.

Table 3. Descriptive statistics, latent correlations and Fornell–Larcker criterion ($N = 302$).

Construct	M	SD	1	2	3	4	5
1. APP	3.67	0.63	(0.735)				
2. CC	3.40	0.66	0.455 ***	(0.714)			
3. PC	4.14	0.58	0.227 **	0.183 *	(0.752)		
4. AR	3.72	0.66	0.182 *	0.087	0.428 ***	(0.702)	
5. TR	3.44	0.68	0.324 ***	0.367 ***	0.101	0.257 ***	(0.769)

Note: M and SD are for item-mean composite scores (1–5). Off-diagonal values are latent correlations from the CFA; diagonal values in parentheses are square roots of AVE. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 4. Heterotrait–monotrait (HTMT) ratios.

Construct	APP	CC	PC	AR
CC	0.462			
PC	0.239	0.183		
AR	0.187	0.086	0.443	
TR	0.327	0.379	0.093	0.265

Note: All values are below the 0.85 criterion [74].

4.2. Structural Model (H1–H7)

The structural model estimated H1–H7 together with a direct path from APP to TR, which is needed to separate the direct and indirect associations addressed by RQ1. It fitted the data well (Table 5): $\chi^2(221) = 312.68$, $\chi^2/df = 1.42$, CFI = 0.969, TLI = 0.964, IFI = 0.969 and RMSEA = 0.037 (90% CI [0.027, 0.046]). It did not fit significantly worse than the measurement model ($\Delta\chi^2 = 3.34$, $\Delta df = 2$, $p = 0.19$), and it fitted significantly better than a model that omitted the APP → PC and APP → TR paths ($\Delta\chi^2 = 18.56$, $\Delta df = 2$, $p < 0.001$; Akaike information criterion (AIC) = 422.68 vs. 437.24) (Table 5).

Table 6 reports the path estimates, with bias-corrected bootstrap confidence intervals from 5000 resamples. APP was positively associated with CC (H1: β = 0.459, $p < 0.001$) and with PC (H3: β = 0.238, $p < 0.001$). CC was positively associated with TR (H2: β = 0.280, $p < 0.001$), and PC was positively associated with AR (H4: β = 0.427, $p < 0.001$). H1–H4 were therefore supported. CC was not associated with AR (H5: β = 0.022, $p = 0.746$), and PC was not associated with TR (H6: β = −0.089, $p = 0.217$), so H5 and H6 were not supported. AR was significantly associated with TR, but positively rather than negatively (β = 0.239, $p = 0.002$, 95% CI [0.036, 0.421]), so H7 was not supported. The direct path from APP to TR was significant under maximum likelihood (β = 0.178, $p = 0.018$) but not under bootstrapping (95% CI [−0.034, 0.366], $p = 0.110$), so we do not interpret it as a reliable effect. The model explained 21.1% of the variance in CC, 5.6% in PC, 18.5% in AR and 20.8% in TR.

Table 5. Model fit comparison ($N = 302$).

Model	χ^2 (df)	χ^2/df	CFI	TLI	RMSEA [90% CI]	AIC
Measurement model (CFA)	309.34 (219)	1.41	0.969	0.964	0.037 [0.027, 0.046]	423.34
Structural model (H1–H7 + APP → TR)	312.68 (221)	1.42	0.969	0.964	0.037 [0.027, 0.046]	422.68
Restricted model (without APP → PC and APP → TR)	331.24 (223)	1.49	0.963	0.958	0.040 [0.031, 0.049]	437.24

Note: All χ^2 values $p < 0.001$. Structural vs. measurement model: $\Delta\chi^2 = 3.34$; $\Delta df = 2$; $p = 0.19$. Restricted vs. structural model: $\Delta\chi^2 = 18.56$; $\Delta df = 2$; $p < 0.001$. Criteria: $\chi^2/df < 3$ [81]; CFI and TLI ≥ 0.95; RMSEA ≤ 0.06 [83].

Table 6. Structural path estimates (IBM AMOS 26, $N = 302$).

H	Path	B	SE	C.R.	p	β	BC 95% CI (β)
H1	APP → CC	0.433	0.073	5.91	<0.001	0.459	[0.326, 0.566]
H2	CC → TR	0.326	0.091	3.60	<0.001	0.280	[0.093, 0.466]
H3	APP → PC	0.220	0.063	3.47	<0.001	0.238	[0.083, 0.383]
H4	PC → AR	0.479	0.086	5.57	<0.001	0.427	[0.263, 0.589]
H5	CC → AR	0.024	0.074	0.32	0.746	0.022	[−0.127, 0.186]
H6	PC → TR	−0.106	0.086	−1.24	0.217	−0.089	[−0.305, 0.143]
H7	AR → TR	0.253	0.080	3.17	0.002	0.239	[0.036, 0.421]
—	APP → TR (direct)	0.196	0.083	2.37	0.018	0.178	[−0.034, 0.366]

Note: B = unstandardised coefficient; SE = standard error; C.R. = critical ratio; p = maximum-likelihood p-value; β = standardised coefficient; BC 95% CI = bias-corrected bootstrap confidence interval (5000 resamples). R^2: CC = 0.211, PC = 0.056, AR = 0.185, TR = 0.208.

4.3. Indirect Effects (RQ1 and RQ2)

Table 7 reports the indirect effects. The total indirect effect of APP on TR was significant (β = 0.134, bias-corrected 95% CI [0.050, 0.246], $p = 0.002$). AMOS reports bootstrap intervals only for total indirect effects in a model with several mediators, so the specific indirect effects were assessed with Monte Carlo confidence intervals (200,000 draws) based on the unstandardised coefficients and their bootstrap standard errors [67]. The indirect effect through CC (APP → CC → TR) was significant (β = 0.129, unstandardised 95% CI [0.035, 0.263]) and represented almost all of the total indirect effect. The path through PC alone was not significant (β = −0.021, [−0.096, 0.038]). The serial path through PC and AR was small but significant (β = 0.024, [0.003, 0.066]). Because the direct path did not hold under bootstrapping, this pattern resembles the indirect-only pattern described in [86]; because the data are cross-sectional, it is interpreted as an indirect association rather than as established mediation. The total effect of APP on TR was β = 0.312 (95% CI [0.134, 0.470], $p = 0.001$). With respect to RQ2, PC had a positive indirect association with TR through AR (β = 0.102, 95% CI [0.021, 0.230], $p = 0.013$), while its total association with TR was close to zero (β = 0.013, 95% CI [−0.149, 0.207], $p = 0.875$).

Table 7. Direct, indirect and total effects on trust in platform.

Effect	β	B	95% CI	Method
APP → TR: total effect	0.312	0.343	β: [0.134, 0.470]	BC bootstrap
APP → TR: direct effect	0.178	0.196	β: [−0.034, 0.366]	BC bootstrap
APP → TR: total indirect effect	0.134	0.147	β: [0.050, 0.246]	BC bootstrap

Table 7. *Cont.*

Effect	β	B	95% CI	Method
Specific indirect: APP → CC → TR	0.129	0.141	B: [0.035, 0.263]	Monte Carlo
Specific indirect: APP → PC → TR	−0.021	−0.023	B: [−0.096, 0.038]	Monte Carlo
Specific indirect: APP → PC → AR → TR	0.024	0.027	B: [0.003, 0.066]	Monte Carlo
Specific indirect: APP → CC → AR → TR	0.002	0.003	B: [−0.019, 0.026]	Monte Carlo
PC → AR → TR (indirect)	0.102	0.121	β: [0.021, 0.230]	BC bootstrap
PC → TR: total effect	0.013	0.015	β: [−0.149, 0.207]	BC bootstrap

Note: β = standardised and B = unstandardised effect. BC bootstrap = bias-corrected bootstrap interval from AMOS (5000 resamples), reported for the standardised effect. Monte Carlo = interval for the unstandardised specific indirect effect (200,000 draws) [67]; standardised specific effects are products of the standardised paths.

4.4. Moderation Analysis (H8)

H8 asks whether cultural congruence (CC) moderates the association between perceived algorithmic personalisation (APP) and trust in platform (TR). We tested it with PROCESS v5.0 (Model 1), entering APP as the focal predictor (X), CC as the moderator (W) and TR as the outcome (Y). APP and CC were mean-centred before the product term was formed, and inference used HC3 standard errors. Gender, age group, education and region were entered as covariates, that is, as control variables; their coding is given in the note for Table 8. In other words, the moderation effect was estimated while holding these demographic characteristics constant, so that differences in trust between, for example, women and men or between respondents from North and South India could not be mistaken for the APP × CC interaction. The covariates were not hypothesised and are not interpreted as substantive effects.

Table 8. Moderation analysis: cultural congruence (W) as the moderator of the APP → TR association, controlling for demographic covariates (PROCESS Model 1, $N = 302$).

Predictor	B	SE (HC3)	t	*p*	95% CI
Focal predictor and moderator					
APP: perceived algorithmic personalisation (X, centred)	0.219	0.081	2.72	0.007	[0.061, 0.378]
CC: cultural congruence (W, moderator, centred)	0.237	0.086	2.75	0.006	[0.068, 0.406]
Moderation test					
APP × CC (interaction)	0.169	0.146	1.15	0.249	[−0.119, 0.456]
Covariates (control variables)					
Gender: female (vs. male)	0.068	0.074	0.91	0.362	[−0.078, 0.214]
Age group (1–4)	0.000	0.053	0.01	0.995	[−0.103, 0.104]
Education: postgraduate (vs. graduate)	0.070	0.097	0.72	0.474	[−0.122, 0.261]
Education: undergraduate (vs. graduate)	−0.028	0.162	−0.17	0.865	[−0.347, 0.292]
Region: South India (vs. North)	−0.179	0.089	−2.02	0.045	[−0.354, −0.004]
Region: West India (vs. North)	0.001	0.112	0.01	0.991	[−0.219, 0.221]
Region: other regions (vs. North)	−0.010	0.146	−0.07	0.947	[−0.297, 0.277]
Constant	3.393	0.111	30.54	<0.001	[3.174, 3.612]

Note: Dependent variable: TR. X = focal predictor; W = moderator. $R^2 = 0.164$, $F(10, 291) = 5.77$, $p < 0.001$. Moderation test (APP × CC): $\Delta R^2 = 0.014$, $F(1, 291) = 1.33$, $p = 0.249$ (OLS sensitivity check: $F(1, 291) = 4.77$, $p = 0.030$). Covariates are control variables and were not hypothesised. Coding: gender, 1 = female, 0 = male; age group, 1 = 18–20, 2 = 21–23, 3 = 24–26, 4 = 27–29; education, dummy variables for postgraduate and undergraduate (graduate = reference; $n = 20$); region, dummy variables for South India, West India and other regions (North India = reference), where "other regions" combines Central India, East India and respondents who reported only "India". Because the interaction was not significant, simple slopes are not reported.

The model explained 16.4% of the variance in TR, $F(10, 291) = 5.77$, $p < 0.001$. With the covariates controlled, APP (B = 0.219, $p = 0.007$) and CC (B = 0.237, $p = 0.006$) were both positively associated with TR, but the APP × CC interaction was not significant (B = 0.169, SE = 0.146, t = 1.15, $p = 0.249$, 95% CI [−0.119, 0.456]; $\Delta R^2 = 0.014$). H8 was therefore not supported, but given the limited power of this test (Section 3.3) the result is treated as inconclusive rather than as evidence of no moderation. The positive coefficient points to a somewhat stronger APP–TR association at higher levels of CC, but the estimate was imprecise. As a sensitivity check, the same test with conventional ordinary least squares (OLS) standard errors gave $p = 0.030$ ($F(1, 291) = 4.77$); for the reasons set out below, we treat the HC3 result as primary. HC3 was adopted as the primary method of inference during the analysis, on methodological advice, rather than being formally pre-specified. Regression diagnostics explain the difference between the two results. The robust (Koenker) Breusch–Pagan test was not significant ($\chi^2(10) = 15.11$, $p = 0.128$), whereas the normal-theory version was ($\chi^2(10) = 25.83$, $p = 0.004$); because the residuals were not normally distributed (skewness = −0.54, kurtosis = 1.46), the robust version is the more appropriate test. The HC3 standard error of the interaction (0.146) was nearly twice the OLS standard error (about 0.077), which reflects the influence of a few observations: one case had a Bonferroni-significant studentised residual (t = −4.21, $p = 0.010$), and another had the largest influence on the interaction coefficient (DFBETA = 0.086, about half of the coefficient). With these two cases excluded ($N = 300$), the interaction was non-significant with both HC3 (B = 0.065, $p = 0.625$) and OLS (B = 0.065, $p = 0.410$) standard errors, and neither heteroskedasticity test was significant. The OLS result for the full sample therefore depended on two observations. Of the covariates, only residence in South India (relative to North India) was significantly associated with TR (B = −0.179, $p = 0.045$).

5. Discussion

5.1. Summary of Key Findings

Four of the eight hypotheses were supported: H1 (APP → CC: β = 0.459), H2 (CC → TR: β = 0.280), H3 (APP → PC: β = 0.238) and H4 (PC → AR: β = 0.427). H5 (CC → AR), H6 (PC → TR) and H8 (APP × CC → TR) were not supported, and H7 was not supported because the AR → TR association was positive rather than negative (β = 0.239). Table 9 summarises the tests. For RQ1, personalisation was associated with trust mainly through cultural congruence: the indirect effect through CC was significant, the direct effect did not hold under bootstrapping, and the test of CC as a moderator of the APP–TR association was inconclusive. For RQ2, personalisation was associated with greater privacy concern and concern with greater resistance, but concern was not associated with trust, and resistance was positively associated with it. The two pathways appear to involve different platform properties: the cultural fit of outputs on the one hand and data practices on the other. Figure 2 shows the final model.

Table 9. Summary of hypothesis tests.

H	Path	Expected	Estimate	Decision
H1	APP → CC	+	β = 0.459, $p < 0.001$	Supported
H2	CC → TR	+	β = 0.280, $p < 0.001$	Supported
H3	APP → PC	+	β = 0.238, $p < 0.001$	Supported
H4	PC → AR	+	β = 0.427, $p < 0.001$	Supported
H5	CC → AR	−	β = 0.022, $p = 0.746$	Not supported
H6	PC → TR	−	β = −0.089, $p = 0.217$	Not supported
H7	AR → TR	−	β = 0.239, $p = 0.002$	Not supported (opposite sign)
H8	APP × CC → TR	+	B = 0.169, $p = 0.249$	Not supported (inconclusive)
RQ1	APP → CC → TR	Indirect	β = 0.129, 95% CI [0.035, 0.263]	Indirect effect significant; direct effect not significant

Note: H1–H7 and RQ1 were estimated in IBM AMOS 26 (CB-SEM); H8 was estimated with PROCESS v5.0 Model 1 with HC3 standard errors. The RQ1 interval is a Monte Carlo interval for the unstandardised indirect effect.

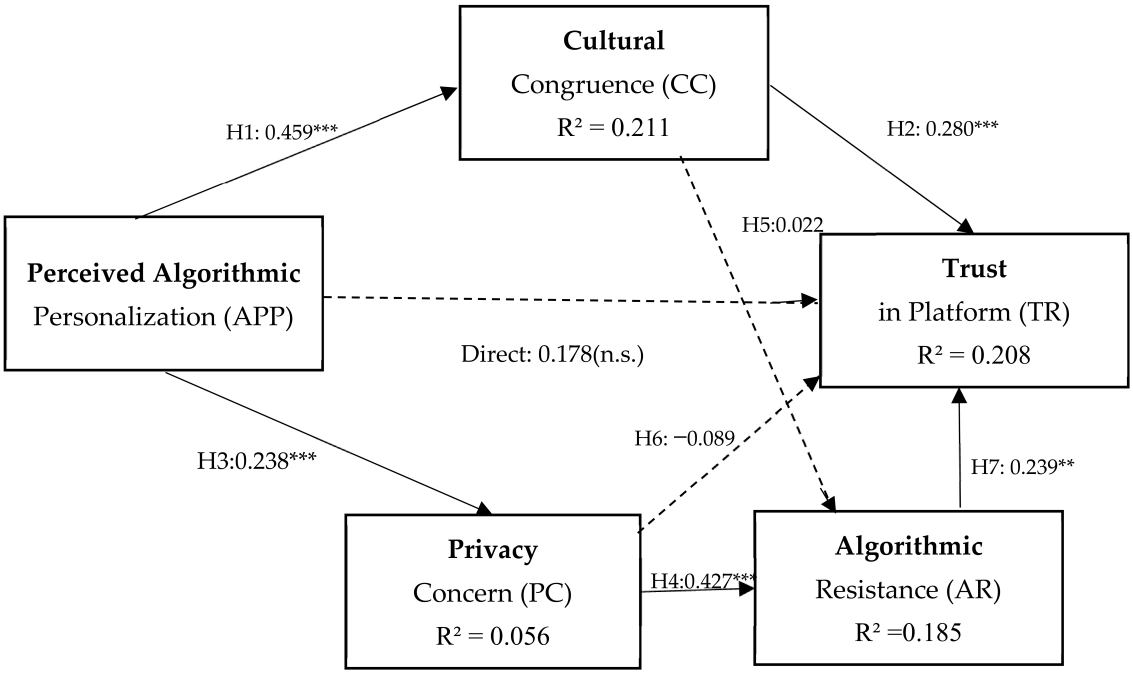


Figure 2. Final structural model with standardised coefficients. Solid arrows are significant paths; dashed grey arrows are non-significant. ** $p < 0.01$, *** $p < 0.001$ (maximum likelihood); n.s. = not significant (bootstrap 95% CI included zero); all significant paths are confirmed by bias-corrected bootstrap intervals (5000 resamples). The direct APP → TR path was significant under maximum likelihood ($p = 0.018$) but its bootstrap 95% CI [−0.034, 0.366] included zero. Indirect effect APP → CC → TR: β = 0.129, unstandardised 95% Monte Carlo CI [0.035, 0.263]. Model fit: $\chi^2(221) = 312.68$, CFI = 0.969, TLI = 0.964, RMSEA = 0.037.

5.2. Comparison with Previous Studies

The substantial association between personalisation and cultural congruence (H1) has no direct counterpart in earlier quantitative work, which has examined personalisation mainly in relation to usefulness, trust and purchase intention [1,18,25]. It is, however, consistent with cross-cultural evidence that AI-enabled personalisation is experienced through a cultural lens [5] and with the argument that widely used AI systems carry

Western cultural defaults [4]. One explanation is that, in a collectivist setting, the individual preferences a system learns carry community content, so accurate recommendations tend to look culturally familiar. Another is that users who already find a platform culturally familiar may judge its recommendations as more personal. With cross-sectional data, the two directions cannot be told apart.

The association between cultural congruence and trust (H2) is consistent with value-congruity research [31], with the social-projection account of trust in collectivist cultures [7] and with Xu and Chen's [32] experimental finding that recommendation fit raises perceived control and, through satisfaction, platform trust. It also goes beyond Hu et al. [18] and Hassan et al. [1], who showed that personalisation builds trust but left cultural fit aside. To these findings our results add an indirect association. Much of the link between personalisation and trust ran through cultural congruence, and once cultural congruence was accounted for, little direct association was left. One interpretation, following the ABI model [44], is that perceived personalisation on its own mainly signals competence, whereas culturally fitting recommendations may also be read as signs of benevolence and integrity. The data did not, however, provide clear evidence for the stronger claim that personalisation is associated with trust only when cultural congruence is high (H8).

On the privacy side, the concern–resistance association (H4) is consistent with McKee et al. [12], who examined why Generation Z consumers adopt ad blockers, private browsers and other anti-tracking measures and linked personalisation–privacy tensions to brand avoidance. It is also consistent with evidence that users respond to narrow or manipulative recommendations with resistance, avoidance and discontinuance [57–59]. The positive association between personalisation and privacy concern (H3) fits research on the personalisation–privacy paradox [12,13,50], although the effect was small ($R^2 = 0.056$). Privacy concern was also high in absolute terms ($M = 4.14$ on a five-point scale), so for this cohort perceiving a feed as personalised and being concerned about the data behind it appear to coexist.

The absence of a significant association between privacy concern and trust (H6) is consistent with hopeful-trust accounts [65] and with Teepapal's [61] finding that privacy concern did not affect engagement with personalised social media. It sits less comfortably with privacy calculus theory [49] and with longitudinal evidence of small but real associations between concern and behaviour [11]. The result for H7 ran against expectation: algorithmic resistance was positively, not negatively, associated with trust ($\beta = 0.239$), and the latent correlation between the two constructs was also positive ($r = 0.257$). A simple explanation follows from the measure itself: three of the four AR items describe privacy-protective behaviours rather than resistance to recommendations (Section 2.5), so the H5 null and the positive H7 association may reflect what AR captured. Another possible explanation is that the behaviours measured as resistance, such as adjusting settings, limiting data and avoiding some recommendations, also work as ways of managing the feed, so users who engage in them may feel more in control of the platform. This reading fits experimental evidence that perceived control over recommendations raises satisfaction and, through it, platform trust [32], and evidence that protective behaviour and privacy attitudes do not map neatly onto each other [63], but our data cannot test it directly. One related pattern is exploratory. Privacy concern had a small positive indirect association with trust through resistance ($\beta = 0.102$), but its direct path was negative and non-significant, which left its total association with trust close to zero ($\beta = 0.013$).

Recent evidence is not entirely consistent, however. In a mixed-methods study of 300 young news users in the United Arab Emirates, Al-Zoubi et al. [87] found that stronger perceived personalisation went with lower perceived diversity and lower institutional trust, which they call an "algorithmic perception paradox". Their setting was news, where users

care about the range and reliability of information. Ours covers entertainment, social and shopping platforms, where fit with the user's own world may count for more. The contrast suggests that the link between personalisation and trust depends on context, and that cultural congruence may be part of that context.

5.3. Theoretical Implications

First, the study extends the personalisation–trust literature by identifying cultural congruence as a construct through which personalisation may be associated with trust in a collectivist emerging market. Hassan et al. [1] show that personalisation strengthens the trust–satisfaction–loyalty chain; the present results suggest that, for this cohort, much of the personalisation–trust association runs through whether recommendations feel culturally fitting. Westjohn et al. [7] show that trust propensity in collectivist cultures operates through social projection from group membership, and Mehmood et al. [5] find that AI-enabled personalisation has different self-concept effects across cultures. Our results are consistent with both, in that the trust-relevant part of personalisation was largely the part that users experienced as culturally congruent. The test of cultural congruence as a boundary condition (H8) was inconclusive. Mediation and moderation accounts are not mutually exclusive, however, and an adequately powered experimental test of the interaction is needed before the boundary-condition account is set aside. This contribution does not depend on whether recommendation systems already draw on cultural signals. APP captures whether recommendations match a user's individual interests, whereas CC captures whether they fit the user's cultural values and lifestyle, and the two were empirically distinct (HTMT = 0.462). The question is not whether algorithms use cultural data but whether users experience the result as culturally fitting, and the results suggest that this experience is associated with trust beyond perceived personalisation itself.

The results also separate the privacy pathway from the trust pathway. Privacy concern was associated with resistance but not with trust. This is in line with hopeful-trust accounts [65], and it extends McKee et al. [12], whose study of Generation Z linked personalisation–privacy tensions to brand avoidance without examining platform trust as an outcome of resistance. It is often assumed that resistance signals distrust, yet here resistance was positively associated with trust. As measured in this study, resistance may partly capture users actively managing their feed rather than withdrawing from it. Future measures should separate the two explicitly. Colnago et al. [63] make a related point: even people who dismiss privacy concerns adopt protective behaviours, which supports a conceptual separation between evaluations of a platform and protective behaviour.

Finally, the PCIT exclusion has implications for measurement. Social identity theory [73] predicts that perceived misrepresentation of the in-group triggers identity threat. In this sample, however, the PCIT items did not separate from the CC items. One possible explanation draws on evidence that large language models encode Western cultural defaults [4]. For Indian Generation Z users, the experience of cultural misalignment and the experience of cultural threat may arrive together, and a single cross-sectional survey may not be able to separate them. Future research should develop behaviourally grounded items that separate the cognitive evaluation of cultural alignment (CC) from the affective experience of cultural threat (PCIT).

5.4. Managerial and Policy Implications

The implications in this section rest on a non-probability sample of young platform users who were enrolled in or had completed higher education, most of them postgraduates (54.3%). They apply to this group and should not be extended to Indian Generation Z platform users as a whole without further evidence. Platform designers and digital

marketers face two distinct problems that call for distinct responses. The first concerns cultural fit. In our data, the association between personalisation and trust ran largely through cultural congruence (indirect $\beta = 0.129$), and the direct association was not reliable. Platforms targeting Generation Z users in collectivist markets could therefore treat cultural alignment as part of personalisation quality rather than as a separate localisation exercise, for example by weighting regional-language content, making recommendations aware of festivals and occasions, amplifying community creators and reflecting local aesthetic conventions. Recommender research shows that such goals can be written into system metrics: the commonality measure of Ferraro et al. [88], for example, rewards exposure to shared cultural content rather than individual relevance alone. Mehmood et al. [5] show that AI-enabled personalisation can both extend and restrict the self, depending on cultural context. Because our design is correlational, platforms should test these implications directly, for example with A/B experiments that vary cultural fit while holding accuracy constant.

Privacy-driven resistance is the second problem. As the PC → AR path shows (H4: $\beta = 0.427$, $p < 0.001$), uncertainty about data practices is linked to circumvention behaviours that limit algorithmic reach. Better cultural alignment does not help here (H5: $\beta = 0.022$, $p = 0.746$). Informational concerns have to be addressed directly. Possible measures include plain-language consent dashboards in India's 22 scheduled languages, "Why am I seeing this?" explanations, and clear data-use disclosures that comply with the DPDPA 2023 [15]. Lyngdoh et al. [21] found that how transparent a firm's privacy policy appears affects information sharing among Indian Generation Z users. Gross [48] shows that privacy concerns centre on collection, control and awareness, and these are the dimensions that the DPDPA's consent provisions deal with. Given the positive association between resistance and trust, platforms also need not treat every use of privacy settings or feed controls as disengagement. Offering such controls may be compatible with trust, although experiments are needed to confirm this.

As a suggestion that the survey did not test, the results may also point to a governance gap that DPDPA compliance alone cannot close. The Act's consent provisions speak to the data-practice concerns that our data link to resistance; they do not address the cultural fit of recommendation outputs, which our data link to trust. In some respects, the Consumer Protection (E-Commerce) (Amendment) Rules, 2026, go further. From 1 January 2027, these rules prohibit e-commerce entities from manipulating search results in ways that mislead users or adversely affect the relevance of results to their search query. They also require sponsored listings to be clearly disclosed, oblige platforms to comply with the Guidelines for Prevention and Regulation of Dark Patterns, 2023, through a yearly self-audit, and bar marketplaces from using consumer information for specified purposes without express and affirmative consent [89]. The provisions regulate how results are ranked, labelled and targeted. On whether recommendation outputs are culturally representative, they too say nothing. At present, no provision obliges platforms to show that their recommendations reflect the regional, linguistic and community diversity of the populations they serve. One possible route is to give users more say over the logic of their feeds, an idea sometimes called algorithmic sovereignty [90]. Another is for India's emerging AI governance framework to consider a cultural representation standard as a further dimension alongside accuracy and fairness. Because the sample consisted mainly of postgraduates, this suggestion is offered for discussion only. Whether users with less formal education show the same pattern is not known.

In practice, the two-pathway pattern means that DPDPA compliance and cultural investment solve different problems. A platform that spends on cultural localisation but neglects consent transparency will probably still face algorithmic avoidance. A platform that fully complies with the DPDPA but ignores cultural alignment may earn less trust than

it could. Managers who see the two as interchangeable answers to "user concerns" may end up under-investing in both.

5.5. Limitations and Directions for Future Research

The results are subject to several limitations. First, because the design is cross-sectional, no causal inferences can be drawn. The APP → CC path in particular may partly reflect reverse causation, since users who already find a platform culturally familiar may judge its recommendations as more personal. The indirect effect should therefore be read as consistent with a mediating mechanism, not as proof of one. Second, every construct was measured by self-report in one survey. Our procedural and statistical checks suggest that common method variance does not explain the main associations, but we cannot rule it out. Third, the sample is a non-probability sample concentrated in North and South India (73.8%), almost entirely aged 18–26 and weighted towards postgraduates (54.3%), so the findings should not be generalised to all Indian Generation Z platform users. Fourth, the CC items were developed for this study from Luna and Gupta's [29] framework rather than taken from a validated scale, and AVE for AR (0.493) was marginally below 0.50; future studies should refine both instruments, drawing on McKee et al.'s [12] work on Generation Z avoidance behaviour for AR. Fifth, TR measured general trust in the data practices of the platforms respondents use, rather than trust in a specific platform or in its recommendations, and respondents answered about several platforms at once. Filter 2 did not record which platforms each respondent used, so platform type could not be tested as a moderator, although trust formation may differ between social media, streaming, e-commerce and music platforms. Sixth, AR as measured is mainly privacy-protective behaviour, CC4 expresses a preference rather than perceived fit, and APP1 and CC1 are similarly worded, so part of the APP–CC association may reflect overlapping perceptions measured in the same questionnaire; items were also presented in fixed, labelled sections without randomisation, and the CC items were not examined through cognitive interviews or a pilot test. The sample also under-represents East and North-East India relative to the population. Seventh, H8 was tested with composite scores in a regression separate from the latent model, which ignores measurement error in the interaction term. Power to detect a small interaction ($f^2 = 0.02$) was about 0.69, and the interaction was significant with conventional OLS standard errors ($p = 0.030$) but not with the HC3 standard errors used as the primary inference ($p = 0.249$), and the OLS result depended on two influential observations (Section 4.4). The non-significant result should therefore be regarded as inconclusive rather than as evidence of no moderation. Finally, the specific indirect effects were assessed with Monte Carlo rather than bootstrap intervals, because AMOS reports bootstrap intervals only for total indirect effects in this model.

There are several ways in which future research could extend the model. Replication in other large collectivist digital markets, such as Indonesia, Nigeria, Brazil and Vietnam, would show whether the cultural congruence pathway to trust is general to collectivist contexts or specific to India. Mehmood et al.'s [5] cross-cultural framework could serve as a starting point for such work. Because CC and PCIT overlapped, qualitative or mixed-methods work is also needed to develop items that distinguish the cognitive evaluation of cultural alignment from the affective experience of cultural threat. Social identity theory [73] and evidence on cultural bias in AI [4] both support this distinction, but our items were not able to capture it. Digital literacy is another candidate moderator of the APP → CC path, because more digitally literate users may draw a sharper line between technical accuracy and cultural accommodation.

What is needed most is an experimental test of the proposed mechanism. A between-subjects design could vary personalisation accuracy and cultural congruence independently,

for example with simulated feeds. Such a design would show whether cultural fit causes trust, and it would give the moderation hypothesis, which the present data could not confirm, an adequately powered test.

Two methodological extensions would also be useful. Future work could pair a CB-SEM study of the structural paths with a second study using fuzzy-set qualitative comparative analysis (fsQCA). That would show which configurations of conditions produce high trust, for example whether high APP, high CC, low PC and low AR together are necessary or sufficient, which variance-based SEM cannot establish. Longitudinal panel data following the same users across several waves would also test whether the weak link between resistance and trust persists or whether sustained resistance eventually erodes trust, which hopeful-trust theory [65] suggests it should not.

6. Conclusions

Among Indian Generation Z platform users, perceived algorithmic personalisation was associated with platform trust mainly through cultural congruence; because the data are cross-sectional, this indirect association is consistent with, but does not establish, mediation. Personalisation was positively associated with cultural congruence, cultural congruence was positively associated with trust, and the indirect effect of personalisation on trust through cultural congruence was significant, whereas the direct association did not hold under bootstrapping. The test of cultural congruence as a moderator of the personalisation–trust association was inconclusive. In the privacy pathway, personalisation was associated with greater privacy concern and concern with greater resistance, but concern was not associated with trust, and resistance was, unexpectedly, positively associated with trust. The exclusion of PCIT suggests, finally, that cultural misalignment and cultural identity threat are hard to separate for this population with the present items, and better-differentiated measures are needed.

For platform strategy and governance, the results suggest that trust in platforms' data practices among Generation Z users in India is associated with whether recommendations are experienced as culturally fitting, not only with perceived personalisation. Privacy governance addresses the concerns associated with resistance but is unlikely on its own to build trust, because the two involve different platform properties. For India's AI governance agenda, we suggest, as a proposal that this survey did not test, consideration of a cultural representation standard for recommendation systems, a dimension that neither the DPDPA 2023 nor the amended E-Commerce Rules [89] currently address. These conclusions are limited by the cross-sectional design and by a non-probability sample made up mainly of postgraduates. The policy suggestions in particular apply, at most, to young users who are in or have completed higher education, and they should be tested with broader samples and with experimental and longitudinal designs before they are applied more widely.

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Appendix A. Full Wording of All Measurement Items and Standardised CFA Loadings

Table A1. Full wording of all measurement items and standardised CFA loadings.

Item	Wording	Loading
APP1	The recommendations I receive on digital platforms accurately reflect my interests.	0.753
APP2	The advertisements and suggestions I see online are relevant to my preferences.	0.746
APP3	Personalised recommendations help me discover content I enjoy.	0.722
APP4	Overall, personalization enhances the usefulness of digital platforms for me.	0.739
APP5	I believe that algorithms understand my needs and preferences well.	0.713
CC1	The content I receive from digital platforms reflects values familiar to my culture.	0.681
CC2	The recommendations I receive feel consistent with Indian traditions and lifestyles.	0.765
CC3	The tone and style of personalised content align with my cultural values.	0.775
CC4	I prefer digital platforms that are sensitive to my cultural background.	0.624
CC5	Many Western apps fail to represent local cultural values.	Removed
PC1	I am concerned about the amount of personal information collected by online platforms.	0.720
PC2	I feel uneasy when websites request personal details about me.	0.776
PC3	I worry that my personal data may be misused by digital platforms.	0.841
PC4	I am uncomfortable with apps tracking my online behaviour.	0.741
PC5	I believe that personalization often invades my online privacy.	0.674
AR1	I use fake or incomplete information to protect my privacy online.	Removed
AR2	I regularly adjust my privacy settings to control data collection.	0.678
AR3	I use tools such as ad blockers or private browsing modes to avoid being tracked.	0.735
AR4	I avoid using platforms that over-personalise advertisements or recommendations.	0.707
AR5	I consciously limit the amount of data I share on apps and websites.	0.687
TR1	I trust websites I use to be honest with their users.	0.778
TR2	I trust websites I use to use personal data as promised.	0.747
TR3	I believe the websites I use are competent in protecting users' personal information.	0.739
TR4	I believe websites I use generally act in users' best interests.	0.761
TR5	Overall, I trust the websites I regularly interact with.	0.816
PCIT1	Western digital platforms often overlook Indian cultural values.	Removed
PCIT2	Global platforms promote Western lifestyles that do not align with our traditions.	Removed
PCIT3	The growing influence of Western apps weakens our cultural identity.	Removed
PCIT4	Using Western-designed platforms makes me feel less connected to my roots.	Removed
PCIT5	Technology is gradually eroding traditional Indian values and practices.	Removed

Note: Items were rated from 1 (strongly disagree) to 5 (strongly agree). All loadings $p < 0.001$. The table lists every item administered, in questionnaire order, with the wording respondents saw. Items marked "Removed" were dropped during the CFA (Section 3.1). CC5 loaded with the PCIT items; PCIT (perceived cultural identity threat; PCIT1–PCIT5) did not separate from CC and was excluded before the hypotheses were tested; AR1 was also removed during the CFA. Each block of items was presented under a construct title with a one-sentence description (Section 3.4).

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