

Demographic Differences in OTT Continuance Intention and Perceived Algorithmic Intrusiveness

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Abstract

Streaming platforms in India now compete less for new users and more for the ones they already have. Earlier analysis of this dataset showed that price value, personalization, habit, and perceived algorithmic intrusiveness together explain a good part of why subscribers stay. This paper asks a different question: does it matter who the user is? It tests whether the intention to keep using an OTT platform changes with monthly income, and whether users with more education find recommendation algorithms more intrusive. Responses were collected from 311 active OTT users in Alappuzha district, Kerala, using a structured five-point Likert questionnaire, and were analysed with one-way ANOVA and Duncan post hoc tests. Neither demographic mattered. Users in the lowest income bracket reported about the same intention to continue as users in the highest, and perceptions of algorithmic intrusiveness were steady from school-level respondents through doctoral ones. The pattern suggests that once someone is already watching and paying, what keeps them on a platform has more to do with experience and routine than with earnings or qualifications. For platforms, that means pricing plans and messages about data use may not need separate versions for each income or education tier, at least among young, digitally comfortable users like these. The study also shows why the demographic assumptions common in OTT adoption research deserve testing rather than acceptance.

Keywords: Continuance Intention, Algorithmic Intrusiveness, Income, Education Level, OTT Platforms.

Introduction

Over-the-top (OTT) platforms have become the main way people in India watch films and series. Netflix, Amazon Prime Video, Disney+ Hotstar, and JioCinema all compete for the same viewers, and moving from one service to another costs the viewer almost nothing. Because winning a new subscriber is expensive and losing one is easy, platforms care a great deal about continuance intention, which is simply a user's intention to keep using a service (Bhattacharjee, 2001).

The parent study behind this paper surveyed 311 OTT users in Alappuzha district, Kerala, and tested four predictors of continuance intention: price value, perceived personalization, habit, and algorithmic intrusiveness (Vineeth Chandra et al., 2026). Those four explained a substantial share of why users said they would stay. That analysis treated all 311 respondents as one group. It did not ask whether the same answers come from users at different income levels or with different educational backgrounds.

There is reason to think they might not. Bellamkonda et al. (2021) found that income shaped OTT subscription behaviour in India, with affordability acting as a barrier for lower-income viewers.

Choudhary et al. (2023) reported that income and occupation both influenced adoption. Sinha et al. (2024) argued that purchasing power helps explain which millennials commit to a paid subscription. On the algorithm side, Brodsky et al. (2020) found that awareness of how recommendation systems work varies with education and improves with teaching, which raises the possibility that better-educated users notice and resent algorithmic profiling more than others do.

All of that work, however, looks at the decision to start subscribing. This study looks at users who have already started. It asks two questions: whether continuance intention differs across income groups, and whether perceived algorithmic intrusiveness differs across education levels.

Review of Literature

• Income and OTT Behaviour

Income shows up repeatedly as a correlate of OTT use. Bellamkonda et al. (2021) profiled Indian OTT users and found that income and affordability were among the clearest demographic predictors of subscription behaviour. Choudhary et al. (2023) reached a similar conclusion, though they also noted that overall spending on entertainment looked much the same for OTT users and traditional media users. Sinha et al. (2024) studied millennials and concluded that purchasing power helped explain who was willing to pay.

Each of these studies measures a decision made at the doorway: whether to subscribe at all. Price matters most at that moment. Continuance intention is measured later, among people who have already paid and kept watching. Whether income still separates users at that later stage has not been tested directly in this setting.

• Education and Views on Algorithms

A second body of work connects education to how users understand recommendation systems. Brodsky et al. (2020) surveyed college students across shopping, search, and social media contexts and found that algorithm awareness differed by context and rose after teaching. More educated users, on this account, have a clearer picture of how platforms track and predict behaviour. Debora Dhanya and Jaidev (2019) then showed that awareness of personalization can translate into privacy concern and a sense of intrusion, a reaction consistent with psychological reactance theory (Brehm, 1966).

Put together, these two findings point in two directions. Better-educated users might react more strongly to algorithmic profiling because they understand it better. Or they might have simply accepted it as an ordinary part of using digital services, in which case education would show no effect at all. Nobody has tested which holds for OTT recommendations specifically.

Hypotheses

Price value is a core construct in UTAUT2, which treats continued use as partly a judgement about whether a service is worth what it costs (Venkatesh et al., 2012). If a user's income changes how heavily that cost weighs, continuance intention should vary by income group. Following the demographic findings of Sinha et al. (2024) and Bellamkonda et al. (2021):

H₁: Continuance intention differs significantly across income groups.

Psychological reactance theory holds that people resist systems they feel are constraining their choices (Brehm, 1966). If education sharpens a user's understanding of algorithmic profiling, as Brodsky et al. (2020) suggest, that understanding could change how intrusive the recommendations feel. Accordingly:

H₂: Perception of algorithmic intrusiveness differs significantly across education levels.

Method

• Design and Sample

This study uses the cross-sectional survey design of the parent report (Vineeth Chandra et al., 2026). Data were collected from active OTT users living in Alappuzha district, Kerala, through a structured questionnaire. Purposive sampling was used so that only respondents with a current or recent OTT subscription were included. Cochran's formula for infinite populations at a 95% confidence level gave a target of 311 respondents, which was met in full. Table 1 shows how the sample is distributed across the two demographic variables studied here.

Table 1: Distribution of Respondents by Income and Education

Category	Group	n	%
Monthly income (INR)	Below 20,000	192	61.7
	20,001–40,000	67	21.5
	40,001–60,000	19	6.1
	60,001–80,000	16	5.1
	Above 80,000	17	5.5
Education level	School level	13	4.2
	Undergraduate	165	53.1
	Postgraduate	127	40.8
	Doctoral	3	1.0
	Other	3	1.0

Note. Source: Primary data.

• Measures and Analysis

Continuance intention and algorithmic intrusiveness were measured with the same multi-item five-point Likert scales used in the parent study, running from strongly disagree to strongly agree. Continuance intention captured whether respondents intended to keep using their platform, and algorithmic intrusiveness captured how invasive they found its recommendations. Reliability was acceptable for the first scale and good for the second, and skewness and kurtosis for both fell inside the conventional plus or minus one range (George & Mallery, 2010; Hair et al., 2019), so parametric tests were appropriate.

One-way analysis of variance was run twice: once comparing mean continuance intention across the five income groups, and once comparing mean algorithmic intrusiveness across the five education levels. Duncan's multiple range test followed each ANOVA to check whether any pair of group means formed a separate subset.

Results and Discussion

• Income and Continuance Intention (H_1)

Mean continuance intention barely moved across income brackets, running from 3.46 among respondents earning below INR 20,000 to 3.77 among those earning INR 60,001–80,000, against a sample mean of 3.51 (Table 2).

Table 2: Descriptive Statistics for Continuance Intention by Income Group

Income group (INR)	n	M	SD	SE	Min	Max
Below 20,000	192	3.46	0.73	0.05	1.33	5.00
20,001–40,000	67	3.49	0.71	0.09	1.00	5.00
40,001–60,000	19	3.68	0.73	0.17	2.33	5.00
60,001–80,000	16	3.77	0.61	0.15	2.67	4.67
Above 80,000	17	3.71	0.63	0.15	3.00	5.00
Total	311	3.51	0.72	0.04	1.00	5.00

Note. Source: Primary data.

Table 3: One-Way Analysis of Variance for Continuance Intention by Income Group

Source	SS	df	MS	F	p
Between groups	2.82	4	0.70	1.38	.242
Within groups	156.68	306	0.51		
Total	159.50	310			

Note. Source: Primary data.

The ANOVA returned no significant difference, $F(4, 306) = 1.38$, $p = .242$. Because p is well above .05, the null hypothesis of equal means stands.

Table 4: Duncan Post Hoc Test for Continuance Intention by Income Group

Income Group (INR)	n	Subset 1
Below 20,000	192	3.46
20,001–40,000	67	3.49
40,001–60,000	19	3.68
Above 80,000	17	3.71
60,001–80,000	16	3.77
Sig.		.170

Note. Source: Primary data.

Duncan's test placed all five groups in one homogeneous subset ($p = .170$), confirming that no pair of income groups differed meaningfully. H1 is not supported.

This runs against what the adoption literature would predict (Bellamkonda et al., 2021; Sinha et al., 2024). The most likely reason is the stage at which the measure is taken. Affordability decides whether someone signs up. It has much less to say about someone who has already signed up, watched for months, and built the platform into an evening routine. At that point the drivers identified in the parent study, especially habit, appear to work much the same way for a student on a low budget as for a salaried professional.

- **Education and Perceived Algorithmic Intrusiveness (H₂)**

Perceptions of intrusiveness were even more uniform. Undergraduate and postgraduate respondents, who together make up 93.9% of the sample, returned almost identical means of 3.57 and 3.56 (Table 5). The doctoral and "Other" categories sat at the two extremes but contained only three respondents each, with standard deviations roughly twice those of the larger groups.

Table 5: Descriptive Statistics for Algorithmic Intrusiveness by Education Level

Education Level	n	M	SD	SE	Min	Max
School level	13	3.62	0.77	0.21	2.00	5.00
Undergraduate	165	3.57	0.77	0.06	2.00	5.00
Postgraduate	127	3.56	0.87	0.08	1.00	5.00
Doctoral	3	3.75	1.52	0.88	2.00	4.75
Other	3	2.92	1.15	0.67	2.25	4.25
Total	311	3.56	0.82	0.05	1.00	5.00

Note. Source: Primary data.

Table 6: One-Way Analysis of Variance for Algorithmic Intrusiveness by Education Level

Source	SS	df	MS	F	p
Between groups	1.40	4	0.35	0.51	.727
Within groups	208.79	306	0.68		
Total	210.18	310			

Note. Source: Primary data.

The ANOVA again found no significant difference, $F(4, 306) = 0.51$, $p = .727$.

Table 7: Duncan Post Hoc Test for Algorithmic Intrusiveness by Education Level

Education Level	n	Subset 1
Other	3	2.92
Postgraduate	127	3.56
Undergraduate	165	3.57
School level	13	3.62
Doctoral	3	3.75
Sig.		.727

Note. Source: Primary data.

All five education groups fell into a single subset ($p = .727$). H2 is not supported.

The reading that fits best is normalisation rather than reactance. If education mainly taught users to see algorithmic profiling for what it is, the more educated groups should have reported sharper discomfort, as an extension of Brodsky et al. (2020) and Debora Dhanya and Jaidev (2019) would predict. They did not. Across the sample, users seem to have settled on a similar view of recommendation algorithms: mildly intrusive, moderately useful, and not worth leaving over. A second point is worth keeping in mind. Users here are paying for a service they chose, which is a different situation from being shown targeted advertisements on a free social platform, the setting where the reactance finding originally came from.

- **Interpretation of both the Results**

Both tests point the same way. Within this sample, continuance behaviour and views on algorithms hold steady across demographic lines. That is a useful finding, but it needs a careful reading. The sample is young and fairly uniform: two-thirds are aged 18 to 24, half are students, and 61.7% earn below INR 20,000 a month. Education clusters almost entirely in two categories. When the range of a

variable is narrow, the chance of detecting a genuine difference across it falls, and the doctoral and "Other" cells with three respondents each carry almost no statistical weight. These results show no detected difference in a digitally comfortable population, which is not the same as showing that income and education never matter anywhere.

For platforms working with a comparable user base, the practical reading is that segmenting price communication or privacy messaging by income bracket or qualification may add little. The factors that keep users subscribed appear to be experiential rather than demographic.

Conclusion

This study asked whether continuance intention varies with income and whether perceived algorithmic intrusiveness varies with education, using 311 OTT users from Alappuzha district. Neither hypothesis was supported. Income groups reported statistically indistinguishable continuance intention, and education levels reported statistically indistinguishable intrusiveness, with Duncan tests confirming one homogeneous subset in each case.

The limits are those of the parent study plus one of its own. The design is cross-sectional, the sample comes from a single district, the measures are self-reported, and the income and education cells are badly unbalanced at the upper end. Future work could repeat these tests on a larger and more varied sample, add age and gender as further demographic boundaries, and treat income and education as continuous moderators in a regression model rather than as categories in a mean comparison. Given that the parent study found algorithmic intrusiveness to be positively rather than negatively related to continuance intention, it would also be worth checking whether that reversal holds across demographic segments or appears only under conditions this sample does not cover.

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