

Personalized Digital Advertising on Consumer Acceptance Across Generational Cohorts: The Roles of Consumer Profiling, Perceived Relevance, Privacy Concern, and Intrusiveness

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Abstract. Customized online advertisements can be comfy and embarrassing simultaneously. A search may save a consumer time through a recommendation that comes after a search. However, it can also indicate how much a platform has been tracking the activity of that individual. This study employs a dual-path model, as the same advertisement may have a potential benefit, relevance, and two potential costs: privacy issues and intrusiveness. The evidence sources are 13 publications that were created in 2012-2026 and were structured into a theory-driven evidence map; a questionnaire was not included. H1-H7 were used practically as labels to sort findings. They were not tested on a new sample. A number of papers associated personalization or targeting with increased relevance, attention, positive attitudes, clicks, or purchase intention. This trend was not as favorable when data collection was hidden, a personal sign was sensitive, or users had no control. Whereas there are published results regarding the individual relationships postulated under H5 and H6, none of the reviewed studies illustrate the entire mediation process to support the direct effect. There is even less evidence to support H7. Age groups were also focused on Gen Z, with none of the 13 papers designed for Gen Z, Millennials, and Gen X. The testimony was such as to give a tentative response. Beneficial personalization might be reasonable, as long as individuals can comprehend the data practices and do not find it overwhelming.

Keywords: Personalized Digital Advertising, Consumer Profiling, Perceived Relevance, Privacy Concern, Generational Cohorts

1. Introduction

Think of seeing a pair of shoes on the internet on Monday, and the week proceeds with seeing some version of the same advertisement. This is an experience with which I am well acquainted, and this is the problem of this paper. The recurrent advertisement could save time since it can match an already existing interest. It can also be disconcerting as it reveals that the site has a previous search, click, buy, or even location. The traces are aggregated together into profiles that determine who gets an advertisement. The advertisement is thus a sales message and an indication that profiling has

occurred. The worth of that match is not evident. In the counterfactual experiment of Mustri et al., targeted products were more relevant than random products out of 487 subjects, although absolute relevance was meager. The search results might also lead consumers to more familiar vendors or reduced prices [1]. The more appropriate the advertising fit, it does not necessarily imply the outcome is better for the consumer.

This ambivalent result can be found in acceptance studies. According to a survey conducted by McKee et al., 414 Gen Z consumers found out that personalization is beneficial, and privacy regards both the brand response [2]. Hasrama et al. also address the topic of trust, transparency, and privacy, but their inductive analysis is defined as hypothetical and not provided with p-values [3]. There are some conditions that are more evident through experiments. Personalized advertisements increased attitudes and purchase intentions in the research carried out by Lamprinakos et al., whereas clandestine information gathering of the identical kind of advertisement turned out to be more obtrusive [4]. Tucker discovered that reactance would be mitigated and the response to clicks enhanced through privacy controls [5]. A photograph of the participant was used in an eye-tracking study, and 80 percent of the respondents reported that they were uncomfortable with such a personalization [6]. These findings cannot be used to make a general assertion that personalization is either good or bad.

Profiling has another occurrence in a broader technical system. AI-driven advertising has the capability to integrate information across websites, handheld devices, social media, customer databases, travel histories, and feedback and then tailor an audience or a message of creation [7]. The Gen Z Indian consumers interviewed express curiosity and interest, fear, and suspicion [8]. The practice is associated with privacy threats, and a review of targeted advertising reports that there is no pooled meta-analytic effect [9]. Consent, choice, and continuing control is another interview study [10]. The recommendation might be valued and yet disliked by a consumer in terms of the way it was created.

The gaps in the field are indicated by other sources. Transparency and control are highlighted in a review of 56 papers by Labib, but some privacy technologies have little evidence in the real world [11]. Theoretically, Rhodes and Zhou demonstrate that the privacy decision of one individual can have an impact on the offers presented to other consumers [12]. The review of 155 articles indexed in Scopus by Ahuja et al. shows less digitally engaged consumers as under-researched [13]. This is important to a generational study. Gen Z has useful evidence, whereas there is less similar evidence regarding Millennials and Gen X.

The initial sketch posited whether these good and bad roads vary among three generations, and the question remains in this paper. Published evidence is, however, the answer as opposed to a new survey. This study used 13 sources and read them using the original framework and categorized each suggested relationship based on the type of evidence that is factual. Some of the links are direct; the rest of the links are conditional or indirect. The comparison of the three cohorts is not done. That is why the answer and the point at which the 13 papers cease to be informative are reported in this research.

Primary research question: How does personalized digital advertising affect consumer acceptance, and how do the effects differ among Generation Z, Millennials, and Generation X?

Sub-question 1: How do consumer profiling and personalized recommendation mechanisms improve perceived ad relevance?

Sub-question 2: How do privacy concerns and perceived intrusiveness reduce acceptance of personalized advertising?

Sub-question 3: Does generational cohort moderate the relationships between perceived relevance, privacy concern, intrusiveness, and advertising acceptance?

2. Literature review and theoretical framework

2.1. Consumer profiling and personalized recommendation mechanisms

Consumer profiling can be best understood as a series. A platform initially captures declared, behavioral, contextual, or transactional information. It then aggregates those cues into a profile or prediction, categorizes the user into a segment, chooses an advert, and it can vary its product, text, image, timing, or channel. Mogaji et al. conceptual model explains how AI can facilitate these stages [7]. It comes in handy to explain the mechanism, but alone it does not demonstrate that an AI-generated ad alters acceptance.

The notions of targeting and personalization are similar but not the same. Targeting is who will see the advertisement; personalization will alter the message or offer based on information about the person receiving it. Tucker distinguishes between personalized copy and advertising, which is simply targeted [5]. Malheiros et al. change the cue displayed in the creative itself, between a holiday destination and age, name, and photograph [6]. Lamprinakos et al. differ in terms of personalization and the delivery of the information either formally or monitored covertly [4]. These mechanisms are thus coded independently in this review. They are also introduced to the same upstream paradigm due to the fact that both of them utilize profile data to enhance the consumer-ad fit; targeting evidence is not perceived as evidence that consumers found the creative itself to be personalized. The designs indicate that consumers consider the implied data practice and the match together.

Ahuja and colleagues put the algorithm in a broader framework of AI attributes, consumer attributes, consumer reactions and attitudes, firm-specific decisions, and situational factors [13]. This is relevant to the current model. Acceptance is not directly determined in the profile. It alters the message that the consumer is viewing, and the response is influenced by the relevance, privacy interpretation, prior experience, and situational context.

2.2. Benefits of personalized digital advertising

The benefit pathway proposed is initiated with the perception of relevance. A message that aligns itself with an existing task or preference can decrease the amount of search and also make the advertized alternative more accessible to consider. Products that were targeted in the study by Mustri et al. proved to be more applicable and offered more purchase intentions in comparison to random products [1]. Lamprinakos et al. discovered that the attitude and purchase intentions were better with personalized ads as opposed to non-personalized ads [4]. The cue used in the study by Malheiros et al. was not only applicable in the task of booking, but it was also more comfortable than the highly identifying cues [6]. The relevance is thus a positive aspect that the studies back, but not the boundless use of data.

The result is also important. Attention, attitude, intent to buy a particular product, brand loyalty, and actual consumer welfare are not synonymous. One can win the eye with a cue but not accept it, and a purchase is not an intention. The first difference is presented by the condition of photograph in the study by Malheiros et al.; the second by the price and vendor results in the study by Mustri et al. [6, 1]. H1 and H2 are thus compared with the results of each of the studies, but not all positive measures are considered as a common effect.

2.3. Risks of personalized digital advertising

The risk pathway starts with the revelation of more knowledge than anticipated by the consumer in the ad. A covert collection, an identity signal that is sensitive, an inference that is surprising or the lack of control may lead to a feeling of privacy intrusion and perceived intrusion. Covert collection was used to increase the intrusiveness in the study by Lamprinakos et al. [4]. In the study conducted by Tucker [5], weird personal information was more apt to lead to reactance when there was no control of privacy. Names and photographs decreased comfort in the study by Malheiros et al. [6]. It is not merely that data have been used, but what data have been used, how they have been acquired, and whether their use is sensible in the task at hand.

The privacy calculus theory can be used to understand the reasons why there are benefits and risks. Customers can choose to trade off the expected convenience with the expected privacy loss instead of taking all personalization or none. This coexistence is directly supported by McKee et al.: perceived personalization benefit was correlated with positive brand responses, whereas the privacy concern was correlated with them in a negative way [2]. Interest, along with surveillance issues and ineffective consent, were also reported by the participants of the interview [8, 10].

Agency alters the determination. The overt collection is more effective than the covert in the study by Lamprinakos et al., and more privacy control reduced reactance in the study by Tucker [4, 5]. The subjects of the study by Roshith et al. gave consent, choice and control against the complete depersonalization [10]. At the review level, Labib comes up with the same conclusion [11]. The transparency and control do not eliminate all the concerns, but they provide the consumer with an opportunity to comprehend the exchange and change it.

2.4. Differences among consumer groups

The original framework defines three cohorts: Generation Z aged 18-29, Millennials aged 30-44, and Generation X aged 45-60. These are operational definitions for the proposed study rather than universally fixed generational boundaries. A comparative analysis should hold the stimulus and measures constant; otherwise, culture, education, platform use, income, or product category may be mistaken for age.

The available evidence is concentrated in Gen Z. McKee et al. sample 414 U.S. Gen Z consumers, and Peter et al. and Roshith et al. sample 40 and 20 Indian Gen Z consumers [2, 8, 10]. Hasrama et al. include adults aged 18-64 but do not report inferential comparisons among the three cohorts [3]. The studies provide useful within-group evidence, including gender and privacy-orientation differences, but they do not establish a generational ranking.

The corpus contains stronger evidence for psychological and situational differences. In the article by Lamprinakos et al., emotion had an impact on the magnitude of personalization effects [4]. Responses to odd personal information were altered in the presence of privacy controls in the study by Tucker, and comfort in the presence of cue sensitivity in the study by Malheiros et al. [5, 6]. These findings support consumer heterogeneity, while Ahuja et al.'s review confirms that older and less digitally engaged groups remain a gap [13]. H7 is therefore posed as a non-directional hypothesis, exactly as in the original outline.

2.5. Conceptual framework and hypotheses

The conceptual framework combines the benefit and risk pathways. Perceived personalization is the independent variable. The proposed positive path, which is perceived relevance, and the proposed

negative path, which is the privacy concern and perceived intrusiveness, are carried by perceived relevance and privacy concern, respectively. The results are advertising acceptance, click intention, and purchase intention. Generational cohort is a moderator, and digital literacy and experience with personalized advertising before are the control variables.

In Figure 1, it is anticipated that perceived personalization will affect advertising acceptance through two parallel paths. Personalization exerts a positive effect on perceived relevance on the benefit route, which helps in acceptance, click intention, and purchase intention. Risk route: with personalization, privacy concerns and perceived intrusiveness considerations increase, compromising the same results. The strength of both routes could depend on the generational cohort, and digital literacy and previous experience are control variables, as they can also influence consumer responses. The figure thus indicates why the impact of personalization cannot be considered as either positive or negative.

The hypotheses below remain the same as in the original outline; however, they play a different role in this review. They are theory-driven propositions to be used in organizing the evidence map, rather than statistically tested on a new common sample. H1-H4 are propositions of a direct-effect nature, which demand empirical support for the mentioned connection. Mediation propositions H5-H6 demand a formal mediation test of direct support to be reported as indirect or otherwise; evidence of links between individual components is categorized only as indirect. H7 needs the common-design comparing the strength of the paths in the three cohorts. These guidelines are stated in advance in order that various types of evidence not be assessed to some undefined criterion.

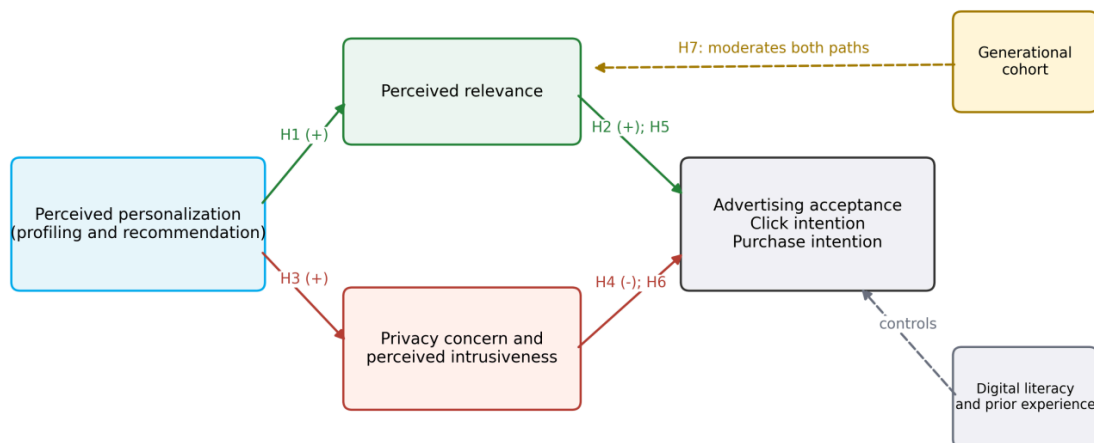


Figure 1. Dual-path analytical framework retained from the original outline

H1: A higher perceived level of personalization is positively associated with perceived ad relevance.

H2: Perceived ad relevance is positively associated with advertising acceptance and purchase intention.

H3: A higher perceived level of personalization is positively associated with privacy concern and perceived intrusiveness.

H4: Privacy concern and perceived intrusiveness are negatively associated with advertising acceptance.

H5: Perceived relevance mediates the positive relationship between personalization and advertising acceptance.

H6: Privacy concern and perceived intrusiveness mediate the negative relationship between personalization and advertising acceptance.

H7: The strengths of the benefit and risk pathways differ significantly across generational cohorts. This hypothesis is non-directional because prior studies report mixed age-related responses.

3. Methodology

3.1. Theory-driven structured review and source corpus

This paper is a structured review and evidence map that is driven by a theory. It was predetermined in its evidence base: the same 13 articles chosen in the assignment, all of which are from 2012-2026. This study has read all the documents to the end and retained all 13, even in instances where a certain source had poor methods or unreported information. No fresh survey, interview, experiment, or recruiting of participants occurred. H1-H7 are no longer relevant as hypotheses that are tested on a new sample. They are applied as questions, which assist in organizing the literature.

This cannot be referred to as a comprehensive systematic review. The 13 items were not based on a new, reproducible database search and screening process. These are laboratory and field experiments, cross-sectional surveys, qualitative interviews, reviews, a conceptual advertising model, and a formal economic model. This diversity is helpful in making comparisons of mechanisms, but it eliminates a traditional meta-analysis. The outcomes of fixation time, attitude, clicks, purchase intention, loyalty, interview themes, prices, and consumer surplus differ and were not pooled.

3.2. Construct boundaries and evidence coding

For each source, this research recorded its design, sample or document base, country, age group, advertising mechanism, data collection method, outcomes, reported figures, and main limitation. This research kept targeting and message personalization separate. Targeting concerns who or what is selected for an ad; message personalization concerns how the creative is changed for a particular recipient. Both fit the wider process of profile-based tailoring, but a targeted-versus-random comparison only shows delivered relevance. It does not automatically prove that the consumer experienced the creative as personalized. This research also treated overt or covert collection and weak or strong identity cues as conditions of data practice and cue intensity.

These outcomes could not be treated as substitutes. A person may notice an ad without finding it relevant, and may find it relevant without clicking or buying. This research therefore recorded relevance, attention, clicks, and purchase-related responses separately. This research used causal wording only for randomized or field-experimental comparisons. Survey coefficients are described as associations. Interview findings are treated as participant accounts, while review papers and models provide secondary or theoretical evidence.

3.3. Evidence-mapping rules and ethics

Figures that were included in the entire text were copied into the evidence map. In this study, missing p-values or repair inconsistencies in a source were not estimated. This study predetermined four labels of evidence before making a comparison of the studies. By direct convergent evidence, it is meant that two or more independent empirical sources have looked at the said connection and have indicated the same overall direction. The direction is said to be conditional when it is

contingent on a certain cue, practice of data, or environment. H5 and H6 require an indirect-effect test to be directly supported; when studies only provided the individual connections in the chain, this study termed them as indirect evidence only. H7 will demand a similar test of the three cohorts. Had there not been that design, it was said to be an inadequate comparative evidence. A source that did not test a proposition was not then counted against it.

The research gathered no identifiable information, as only published or public material, which was secondary, was utilized. The ethical problem is primarily the reporting problem: quotes of the results should be correct, causal and associational statements should be kept apart, and weak evidence should be kept in sight.

4. Results

4.1. Source characteristics

The 13 sources constitute a mixed evidence base. Five include an experimental or field-experimental element, two report surveys, two are based on a qualitative interview with Gen Z respondents, three review studies, one constructs a conceptual advertising model, and one provides a formal economic model. Certain sources could belong to more than one category, and therefore Table 1 gives the design that is most applicable in this synthesis and indicates the limit of the evidence provided by each source.

Table 1. Design, population, and evidential boundary of the 13 sources

Ref.	Design and reported data	Population or context	Use and evidential boundary
[1]	Online within-subject experiment; N = 487; 1,169 usable targeted products plus matched search and random products	U.S. adults aged 18–75	Direct relevance, price, and vendor-quality evidence; conference draft; replication and latent-utility work reported as ongoing
[2]	Cross-sectional survey and structural equation model; N = 414	Gen Z students at two Midwestern U.S. universities	Direct associations within Gen Z; convenience sample and cross-sectional design do not establish causality or age-cohort differences
[3]	Mixed-method report; survey counts indicate N = 200; interview N not stated	Adults aged 18–64; mean 39.93, SD 14.01	Descriptive themes only; regression described as hypothetical, p-values absent, and positive-class prediction failed
[4]	Two randomized experiments; N = 139 and reported N = 126	Greek undergraduates; online adult sample	Direct ad-type and emotion contrasts; Study 1 below planned N = 165; Study 2 exclusion wording is internally ambiguous
[5]	Field/natural experiment: 79 campaigns, 1.2 million unique users, 1,995 clicks; online experiment N = 240	Social-network users; nonprofit advertising	Direct click behavior plus reactance mechanism; platform, nonprofit, timing, and persistence limit generalization
[6]	Laboratory eye-tracking study; N = 30; usable fixation data n = 25	Adults aged 19–55 in a holiday-booking task	Direct attention and comfort evidence; small, non-representative sample and first exposure
[7]	Conceptual AI/ML advertising model; no participant sample	Web, mobile, social, CRM, journey, and customer-feedback data	Explains the data-to-creative mechanism; does not test an advertising effect

Table 1. (continued)

[8]	Semi-structured interviews and thematic analysis; N = 40	Indian Gen Z aged 18–27	Perceived emotion and brand experience; purposive, exploratory sample and recalled rather than real-time emotion
[9]	Self-labelled meta-analysis; PDF reports 25 studies, journal page reports 12; no pooled effect	Targeted advertising and privacy studies	Narrative background only because corpus counts conflict and meta-analytic statistics are absent
[10]	Semi-structured interviews and reflexive thematic analysis; N = 20	Urban, educated Indian Gen Z aged 19–27; M = 23.4, SD = 1.93	Consent, choice, and control themes; small context-specific sample, possible priming, and no causal test
[11]	PRISMA systematic review; 56 papers; 50 quantitative and 6 qualitative; 42 rated high and 14 moderate	AI personalization, blockchain privacy, and digital marketing; 14 studies from India	Secondary synthesis; geographic concentration and limited real-world hybrid-system evidence
[12]	Formal economic model; no empirical participant sample	Personalized recommendations, prices, product design, and privacy choice	Explains market externalities and consumer surplus; predictions are theoretical, not observed effects
[13]	Bibliometric and systematic review; 155 Scopus articles from 1,444 initial records, 2016–2026	AI-driven marketing tactics and consumer behavior	Field-level mechanisms and gaps; Scopus-only, English-only, and review-level evidence

4.2. Benefit pathway: evidence for H1 and H2

The literature has direct convergent support in line with H1, but does not blur the line between targeting and message personalization. Mustri et al. carried out their research on 487 participants who gave 1,461 links to ads of which 1,169 were found to fit the criteria and compared to matched search and random products [1]. This is first-hand proof that the relevance sent by profile-enabled targeting was delivered, rather than that participants felt that the creative was personalized. In Study 1 of Lamprinakos et al., personalized advertising boosted mean attitude and purchase intention by 1.18 points (to 5.22) and 1.44 points (to 4.81) on seven-point scales, respectively [4]. The cue of the holiday-destination used in the study provided by Malheiros et al. is also a sign that the information about a task may cause interest without the unpleasant experience like that caused by a photograph [6]. The overall movement of these varying mechanisms of operation is a more fitting consumer-ad fit, despite the fact that the targeted products, even in the work by Mustri et al., were still small in terms of relevance and compared to the search condition [1].

Direct convergent evidence also exists in the literature in line with H2, the difference being between intention and behavior. Relevance revealed the relative advantage of targeted compared to random products in the Mustri et al. study and the personalized condition in the Lamprinakos et al. study enhanced attitudes and purchase intentions [1, 4]. Tucker supplies the strongest behavioral outcome [5]: 79 campaigns reached 1.2 million unique users and received 1,995 clicks; after stronger privacy controls were introduced, personalized ads received a markedly stronger click response. The field setting involved nonprofit advertising during a specific policy change, so the magnitude should not be generalized to every commercial campaign.

Attention alone is insufficient evidence of acceptance. In a 30-person eye-tracking task, usable fixation data were available for 25 participants [6]. The Photo-based ad garnered 13.0 seconds of fixation, as opposed to 7.2 seconds of fixation on the standard-picture ad, but the photograph had the lowest comfort rating, and 80 percent stated that they felt uncomfortable about it. The outcome justifies a gain in noticeability, as well as the motive behind H2 having to be evaluated by attitude or intention, not by attention alone.

Table 2. Selected quantitative results reported in the direct empirical sources

[Ref.] Source	Comparison	Exact result reported
[1] Welfare comparisons	Ad versus search	Logged monthly visits: $M = 15.82$ vs. 17.77 , $t(2154) = -14.2068$, $p < .001$. SiteJabber ratings: $M = 3.41$ vs. 3.53 , $t(1846) = -2.62$, $p = .004$. Search prices averaged 10% lower, $t(1168) = 3.58$, $p < .001$. For 609 identical products, ad price was 7.75% below mean search price but 7.9% above minimum search price, both $p < .001$.
[2] Gen Z privacy calculus	Standardized model paths	Privacy concern $\rightarrow$ non-personalized brand avoidance: $\beta = -.108$, $p < .05$; privacy concern $\rightarrow$ personalized brand loyalty: $\beta = -.161$, $p < .001$. Personalization benefit paths: $\beta = .121$, $p < .01$ and $\beta = .452$, $p < .001$, respectively.
[4] Personalization and collection	Randomized ad contrasts	Study 1 attitudes: 5.22 vs. 4.04 , $F(1,135) = 55.83$, $p < .001$, $\eta^2 = .29$; purchase intention: 4.81 vs. 3.37 , $F(1,135) = 58.08$, $p < .001$, $\eta^2 = .30$. Study 2 covert vs. overt intrusiveness: 4.00 vs. 3.32 , $F(1,121) = 5.81$, $p = .017$, $\eta^2 = .05$; overt vs. covert purchase intention: 5.59 vs. 4.78 , $F(1,122) = 14.68$, $p < .001$, $\eta^2 = .11$.
[5] Privacy control	Field and online experiments	Field interaction increased modeled percentage daily click-through rate by .024 against a .007 pre-policy personalized-ad baseline. In the $N = 240$ experiment, unique-data $\times$ privacy-control coefficients were $-.730$ for reactance ($p < .05$), 1.212 for favorable ad response ($p < .01$), and $.994$ for click intention ($p < .05$).
[6] Personal cue intensity	Photograph vs. less personal cues	Photo ad fixation: 13.0 vs. 7.2 seconds, $t(24) = 3.2$, $p = .003$. Mean comfort: destination 4.0 , age 2.9 , name 2.3 , photo 1.7 ; 80% reported discomfort with photo-based ads.

4.3. Risk pathway: evidence for H3 and H4

The literature gives conditional evidence that is in line with H3. It does not demonstrate that all personalization increases necessarily make privacy an issue. It demonstrates a more particular trend: the risks are increased when the personalization is based on hidden gathering, atypical personal data, or highly identifying signals. In Lamprinakos et al., the perceived intrusiveness went up to 4.00 with covert collection as opposed to 3.32 [4]. In Malheiros et al. research, the age, name and photograph comfort with holiday destination decreased to 4.0 to 2.9 [6]. These contrasts validate the direction suggested under boundary conditions that can be identified.

H4 convergent evidence is given in the literature on multiple designs. Personalized brand loyalty had a negative relationship with privacy concern [2]. In a study by Tucker, the abnormal personal information produced a greater reactance when there was no privacy control [5]. The pattern of discomfort in the research by Malheiros et al. is intrusiveness as compared to lower acceptability, and the interview research by Peter et al. and Roshith et al. relate perceived surveillance, lack of clarity in consent, and the absence of control to suspicion or resistance [6, 8, 10]. The qualitative results do not have an effect size, but their direction is consistent with the quantitative results.

H3 and H4 do not account for an added cost due to consumer welfare. In the study by Mustri et al., the average search prices were less by 10 percent lower than advertised prices [1]. The advertised price was 7.75% lower than the average search price but 7.9% higher than the lowest price on the first page of search results out of 609 identical products offered by various vendors. An individualized advertisement can then be viewed and may not provide the optimal, readily noticeable bargain.

4.4. Mediating pathways: evidence for H5 and H6

H5 is only indirectly supported in accordance with the mediation rule of the methodology. Relevance is the mechanism proposed by Mustri et al. as the advantage of targeted over random products [1], and Lamprinakos et al. demonstrate a chain from a personalized condition to more positive cognitive responses, attitude, and purchase intention [4]. McKee et al. also find a positive association between perceived personalization benefit and personalized brand loyalty to be strong and positive [2]. These component connections fit into the suggested pathway, although none of these reported findings support the indirect impact of personalization on acceptance via perceived relevance in a single model. The review does not thus purport to have proven that mediation has been proven.

H6 is also only indirectly supported. The data practice, intrusiveness, and lesser advertising reactions are related to the covert-collection experiment in the study by Lamprinakos et al. [4]. A randomized survey of 240 participants by Tucker demonstrates that the control of privacy decreased reactance and enhanced positive response and click intention when atypical personal information was involved [5]. More personal cues correlate with discomfort, as Malheiros et al. associate [6]. The links between the components have been consistent with the negative mechanism, and the reviewed findings have no indirect effect of personalization on acceptance via privacy concern or intrusiveness. H6 is thus a theoretically but not empirically validated mediation effect.

4.5. Generational comparison: evidence for H7

The corpus does not give enough comparative evidence on H7 since the common-design comparison that would be needed is missing. The 414-subject design of the structure in the research by McKee et al. just examines Gen Z [2]. Gen Z is also studied in the two Indian interview studies, and purposive samples of 40 and 20 [8, 10] are used. They strengthen the data regarding a single cohort but are unable to approximate the disparities in the strength of the paths across Generation Z, Millennials, and Generation X.

Hasrama et al. cover adults 18-64 [3], which is not valid cohort-comparison evidence due to broad age coverage. The regression analysis is clearly stated as hypothetical, p-values are not provided, and no common-model estimates of the three cohorts are presented. These reporting limitations would have precluded the study from bearing the inferential burden of H7 even if age-stratified descriptive results had been reported. The evidence gap is thus demonstrated largely due to the Gen Z-only focus of McKee et al., Peter et al., and Roshith et al. complemented by the overall review of Ahuja et al. [2, 8, 10, 13].

In-group and situational differences are, however, discernible. A higher level of privacy concern was reported among women as compared to men in the study by McKee et al. (4.10 vs 3.83, $p < .01$), and benefit and concern went hand in hand in the same Gen Z sample [2]. A study conducted by Lamprinakos et al. modified the effect of personalization and the collection method by emotion [4]. Privacy control was different in the study of Tucker and sensitivity of a cue was different in the

study of Malheiros et al. [5, 6]. Though these results render the use of cohort moderation a possibility, they cannot replace a direct three-cohort test.

This means that the evidence-map classification is insufficient comparative evidence. H7 is an unproven hypothesis: it is neither approved nor dismissed by the current corpus. The gap is supported by the fact that older and less digitally engaged consumers are identified by Ahuja et al. as a poorly researched group [13]. The idea that Gen Z is more accepting than Millennials or Generation X would go beyond the evidence that can be found.

4.6. Proposition-level evidence map

Table 3 summarizes how the existing literature covers each original hypothesis. The labels classify literature coverage under the pre-specified rules; they are not results from a new common statistical model and do not confirm or reject H1-H7.

Table 3. Literature coverage of the original H1-H7 framework

Hyp.	Proposed relationship	Main evidence	Literature coverage
H1	Personalization -> perceived relevance	[1, 4, 6]	Direct convergent
H2	Relevance -> acceptance / purchase intention	[1, 2, 4, 5]	Direct convergent
H3	Personalization -> privacy concern / intrusiveness	[4-6]	Conditional
H4	Privacy concern / intrusiveness -> lower acceptance	[2, 5, 6, 8, 10]	Direct convergent
H5	Relevance mediates the positive pathway	[1, 2, 4]	Indirect only
H6	Privacy and intrusiveness mediate the negative pathway	[4-6]	Indirect only
H7	Benefit and risk paths differ by cohort	[2, 8, 10, 13]; [3] limited	Insufficient comparative

5. Discussion

5.1. The dual-path model and consumer acceptance

The primary pattern of the evidence map can be used as a conditional response to the primary research question. When personalised digital advertising produces a useful match, acceptance can be increased, but when it produces a sense of concealment, excessiveness, or uncontrollability, the same process can lead to a decrease in acceptance. The pathways of benefits and risks do not offset before consumer response. These are two different assessments of the same experience: Was it useful, and was the platform entitled to know this?

This takeaway explains a seeming inconsistency of results. Respondents in Gen Z will be able to enjoy the benefits of personalization, but privacy concerns remain a predictor of brand response [2]. Curiosity and fear can be reported simultaneously by the participants of the interview [8]. Without requesting the total elimination of personalized advertising, consumers are allowed to object to data practices [10]. Relevance is not, hence, evidence of trust, and privacy concern is neither evidence that the recommendation is of no use.

5.2. What the evidence says about generational cohorts

The initial scheme rightly considers cohort difference to be an empirical query and not an empirical assumption. The literature reviewed advocates the significance of consumer heterogeneity, but not a

league table of generations. The Gen Z studies vary in terms of country, education, and recruitment. The same advertisements and measures were not provided to the older consumers. A cross-study comparison might thus cause confusion between age and culture, numerical literacy, career, experience with the platform, or style of products.

The lack of a direct comparison does not make the cohort focus irrelevant. It determines the exact point where the literature ends. Direct and conditional evidence discusses some sections of the benefit and risk pathways, but the literature is silent on how these factors are moderated by Generation Z, Millennials, and Generation X. This is an evidence-map gap, rather than a result that the cohorts are the same. H7 is not removed, but it is retained and goes as having inadequate comparative evidence.

5.3. Theoretical and managerial implications

Theoretically, the results can be used to support a privacy-calculus model together with the addition of agency as a boundary condition. An advantage-risk calculation modifies when the user is able to comprehend the data source, modify permissions, or decline a type of personalization. It was not only a procedural requirement in the study by Tucker and overt collection in the study by Lamprinakos et al. to control the response to the advertisement [5, 4].

When it comes to advertisers, precision ought to imply the minimum of personal information required to make a useful matching. The holiday-destination result reported by Malheiros et al. indicates that the information that is relevant to the task can be useful without the identity reveal [6]. The explanation of data collection should be short and simple, and permission should be revocable. A user who desires less tracking should be given a true low-personalization choice, whereas a user who does not mind being tailored should be given a choice of what types of data are used.

Evaluation of campaigns should also not be focused on click-through rate. Relevance, attention, attitude, click intention, and purchase intention are important; however, opt-outs, complaints, intrusiveness, vendor quality, price competitiveness, and longer-term trust are also important. The reason why is in the welfare information in the study by Mustri et al.: the well-crafted ad can promote a visible offer that is not superior even though it is below the superior [1].

5.4. Limitations

There are four limitations of this study. First, the evidence base of this review was pre-determined by the 13 documents instead of being identified by using a new reproducible database search and screening protocol; the review is thus organized and constrained, not comprehensive. Second, the sources incorporate various designs and results, and a pooled effect is invalid. Third, the cohort evidence is also focused on Gen Z, U.S. university samples and informed urban Indian participants. Lastly, the sources are not of the same quality. A conference draft is defined as replicated as in the study by Mustri et al., part of the inferential analysis is described as hypothetical as in the study by Hasrama et al., and there are conflicting counts of studies reported but are not pooled as defined in the study by Ali et al. [1, 3, 7, 12, 9].

The new proposition-level classifications can be interpreted as an evidence map, but not as a replacement for a new three-group statistical test. They indicate the points of convergence between independent findings, and that only component associations or conditioning patterns have been reported, with missing evidence. The operationalizations of profile-enabled tailoring in the source studies are also different: targeting an action of selecting a recipient or a product, and message personalization is an action of modifying the creative. The simultaneous mapping of both

mechanisms in a single upstream structure facilitates comparison but results in heterogeneity in the construction. The same H1-H7 model with a shared stimulus and measures in the three cohorts could be tested later, but the latter design is not introduced here as research that has been conducted.

6. Conclusion

The evidence map widely concurs with the main reasoning of the initial sketch. Perceived relevance can be enhanced by consumer profiling and recommendations, relevance can be used to enhance advertising acceptance and purchase intention. Intrusiveness and privacy concerns may also be caused by personalization when data collection is covert, the cue is strongly identifying, or when the user has no control. Direct convergent evidence is present in H1, H2 and H4, whereas H3 is covered by conditional evidence. H5 and H6 are indirectly evidenced to have component links, yet the reviewed results are not a formal mediation.

The cohort question is not determined. The articles, however, indicate that the personalization-privacy conflict is present among Gen Zers. They also complain about gender, emotion, and sensitivity of cues as well as privacy control differences. No one puts Gen Z, Millennials, and Gen X in an equal situation. For that reason, H7 is registered on the list of gaps in comparative evidence instead of a conclusion on the absence of cohort difference. Practically speaking, the most sound lesson is quite meek. The amount of personal data shown in the ad should be as little as the match requires, the benefit must be visible, the reason why the ad was displayed should be mentioned, and the user should be able to alter the permission.

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