

# Consumer Perceptions of Localized and Personalized Digital Marketing Content in Food Delivery Applications

Marakhtanov Mikhail

School of International Management and Business Administration,  
Bauman Moscow State Technical University, Moscow, Russia, 105005.  
mikhali@inno.mgimo.ru

Correspondence should be addressed to Marakhtanov Mikhail : mikhali@inno.mgimo.ru

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**Abstract** – This study examines consumer attitudes toward personalized marketing in food delivery applications, with a focus on the roles of enjoyment, privacy, and trust. Using quantitative cross-sectional survey design, data were collected to evaluate user perceptions of personalized marketing content on digital food delivery platforms. The study is grounded in theories of personalization, privacy calculus, and digital trust, and investigates factors including enjoyment, comfort with data usage, perceived data security, trust, perceived usefulness, and behavioral intention. Descriptive statistical analysis revealed that consumers generally hold favorable attitudes toward personalized marketing due to its convenience and relevance. However, concerns regarding privacy and potential misuse of personal information moderate these positive perceptions. The findings highlight the importance of balancing personalization benefits with transparent data practices and strong privacy safeguards. The study provides practical implications for platform designers and marketers seeking to enhance user trust and engagement in food delivery applications.

**Keywords** – Personalized Marketing, Food Delivery Applications, Privacy Concerns, Digital Trust, Consumer Perception.

## I. INTRODUCTION

Digital food delivery apps (FDA) have been on rise for more than a decade now. Their development and popularity are not only limited to the youthful generation but to everyone with access to a communication device and the internet, whether a PC, tablet, and smartphone. Most of these apps charge a nominal delivery amount depending on the distance of the client's residence from the restaurant. After an order is placed and after an order is collected by valet, the client can also track valets by the live tracking features in the application itself through GPS.

Most of FDA operating in India include Food Pandas, Uber Eats, Zomato, Swiggy, etc. These applications expose consumers to personalized content, such as political messages, music or movies, search results, and social media posts. Customized advertisements, a typical practice among businesses, which offer free digitalized content, also depends significantly on personalization [1]. Firms utilize big data to train techniques, which predict consumers' purchases, clicks, and even voting choices. Whereas personalized content can be helpful and convenient for consumers, it also bears major risks. One of these risks is the establishment of filter bubbles, where consumers are only exposed to digital content, which align with their beliefs and preferences. This can lead to existing biases, and limit information diversity as well as recommendation.

Within the rapidly developing digital landscape, data-based personalization has been viewed as a game-changer to UX (user experience) design. This will employ behavioral intelligence and data analytics to tailor content and interfaces to individual users and make them more satisfying, engaging, and improved UX. The impact of this strategy on business results is high, and literature shows that personalized experiences may lead to a revenue growth of about 10-15%, and a boost of 20-30% in the effectiveness of the market spending. The trend of data-oriented personalization is very common in various digitalized systems. As of 2023, approximately 90% of online businesses are invested in customization, with 58% of investments going towards technology, which supports data analysis and collection for personalized experiences. This pattern is stimulated by consumer expectations, with approximately 80% of users likely to buy from a company that provides customized experience.

Transparency and trust have been introduced as key constructs in the reconciliation of personalized adverts with privacy. Aguirre et al. [2] argue that responsible information stewardship, clear consent approaches, and transparent data management are vital in enhancing long-lasting consumer relationships. They expanded on this by reviewing an ideology known as “contextual integrity” proposing that privacy is not entirely about data control but appreciating contextual norms in its applications. Shin [3] proposed a model to minimize the personalization-privacy trade-offs by integrating behavioral sciences with advertisement design. Their analysis indicates that data minimization strategies, data consent practices, and the idea of perceived fairness can help firms to alleviate cases of privacy. He also assumes that regulatory uncertainty makes the firms take proactive measures and improve the internal transparency, even when the enforcement of these regulations is less in marketplaces.

We are focused on the study of consumer perceptions on customized marketing content in FDA in terms of enjoyment, perceived usefulness, comfort with data, perceived safety, trust, and behavioral intention using the impact of privacy concerns on the overall attitude towards personalization. The remaining part of this paper is organized as follows: Section II describes the study’s theoretical background, which describes key themes such as TAM/HSAM, personalization-privacy trade-off, digital trust and behavioral intentions. Section III provides details about our research design and instrument development, data collection procedures and methodological design. In Section IV, our findings have been critically provided. Lastly, we conclude the study in Section V to highlight the perception of customers when it comes to personalized marketing content in FDA.

## II. THEORETICAL BACKGROUND

### *TAM/HSAM*

Pagnanelli et al. [4] note that there are significant correlations between continuance intention, perceived usefulness (PU), perceived ease-of-use (PEU), service quality and hedonic motivations. Hedonic motives have a positive impact on PU but no significant effect was found on PEU. The quality of service significantly affects both PEU and PU. Moreover, PEU positively affects continuance intention and PU, while PU significantly affects continuance intentions.

Hedonic system acceptance model (HSAM) was designed according to the technology acceptance model (TAM), which highlight that user acceptance is dependent on PU and PEU. PU alludes to the level at which users believe that a certain system would boost performance, while PEU is the level to which a user believes that utilizing a certain system would be less of an effort. Intelligent stores, in essence, are technological applications of IT because consumers adopt intelligent retail technologies to make purchases. In the regard, consumers’ purchase intentions have been partially defined by TAM.

Kim [5] incorporated trust into TAM to review customers’ purchasing intentions in digital shopping. The findings highlight that these intentions are stimulated by PU and PEU of e-business sites. The scholars also identified that PU and PEU are fundamental forecasters of purchase behaviors and purchase intentions in e-business. Thus, TAM is applicable in defining consumers’ buying intentions.

### *Personalisation–Privacy Trade-Off*

Karwatzki et al. [6] provided a structured analysis of personalization-privacy trade-off among users and propose future study prospects. Particularly, their research attempts to discuss common topics within this field, particularly the current factors affecting user behavior and attitude towards disclosing private data. Until today, the results from study by Çınar and Yahya [7] on personalization-privacy inconsistency from 2000-2022 were evaluated and incorporated via a systematic review method. Findings highlight that perceived privacy control and perceived benefits are key drivers while privacy concerns are key barriers towards user self-disclosure behaviors. Trust within the organization can moderate the impacts of precursor variables on the willingness of users to disclose.

The existing technology is aimed at resolving the issue of privacy versus personalization. These combine both differential privacy, identity control based on blockchains, homomorphic encryption, and federated learning. With reference to Robles et al. [8], these solutions enable the utility of data and protect the personal identity. Privacy-protecting solutions combine an extensive range of strategies that would be used to safeguard the confidential data and also improve its use. These solutions operate in the multi-layered spectrum, as a core tool in control privacy threats of digitalized ecosystems. Among the privacy protection pillars recognized by benchmarking, encryption is the process that secures information and data through their conversion to the unreadable form that is not accompanied by the decryption keys. This method will ensure privacy even in an unauthorized accessibility.

According to Fung, Wang, and Yu (9), anonymity refers to the alteration or removal of identifiable attributes in a dataset to safeguard personal identities and to allow an authorized use and access. A method suggested by Kargupta et al. (10) is known as differential confidentiality; it adds noise and randomness to query responses, which protect the confidentiality of important contributions in a variety of data sets and simultaneously improves the accuracy of statistics.

### *Digital Trust and Behavioral Intention*

Sun [11] described a theoretical model of triple perspectives on trust oriented on the theory of planned behavior and recreated actions. This model integrates three segments, which include intention, attitude, and belief. In this case, belief alludes to a typical psychological procedure, which assesses the attributes and features of the other party, such as a person’s opinions or

feelings about something. Secondly, attitude is the readiness state for action or attention. Thirdly, intention refers to active possibilities, which an individual will carry out a task or action being considered.

In reference to a study by Guo [12], digital trust refers to the redefinition of system trust and interpersonal trust by digital system, and is the proceed of system trust and interpersonal trust “transfer” between and within trust pathways. The construction approach of digital trust integrates soft trust establishment approach, and solid trust establishment approach where system/security design are the solid trust construction approaches. Online social capital, digital reputation model, response and transparency, and result gratification are the approaches of soft trust establishment. These two trust establishment approaches coordinate and operate jointly to achieve trust re-establishment within the online community.

Based on the above definitions of trust and online trust, as well as its structure and dimensions, and integrating digital social contexts, this research employs the constructs of emotional and cognitive trust in enhancing the perception of consumers regarding localized and personalized digital marketing content. This enables advertisers within the food delivery sector to enhance practicality, benevolence, honesty, commitment of execution, beliefs, and likes.

### III. METHODOLOGY

#### Research Design and Instrument Development

To achieve a systematic study of the attitudes of consumers towards individualized marketing information in FDA, our study employs survey-based cross-sectional approach, which is highly suitable in retaining perceptual and attitudinal constructs at a single point in time and facilitating statistical comparability between the respondents.

We employed earlier empirical studies related to personalization, privacy calculus, and digital trust, in particular, the theoretical frameworks proposed by Ashrafi, Ahmed, and Shahid [13], and Cloarec, Meyer-Waarden, and Munzel [14], formed the foundation of operationalization of the enjoyment concept, comfort with data use, perceived safety, trust, and behavioral intention.

The survey was formulated in such a manner that it reduced the cognitive burden, and at the same time provided the construct validity, with most of the attitudinal items being measured on a five-point Likert scale with one end having 1 (strongly disagree) to the other end having 5 (strongly agree) according to the established practices of consumer behavior research. In cases where categorical variation was required, the option of multiple-choice questions was included such as the identification of the current issues pertaining privacy. Prior to the full implementation, the instrument was conceptually tuned to ensure that all items are directly connected to the theoretical dimensions that were identified in the literature and reduce construct ambiguity and maximize content validity.

Table 1 indicates the conceptual design of questionnaire, how the constructs and measurement scales and item intent drew in the same direction without empirical evidence.

**Table 1.** Questionnaire and System of Measurement

| Construct                    | Measurement Scale       | Objective of Measurement                                     |
|------------------------------|-------------------------|--|
| Enjoyment of personalization | 5-point Likert scale    | Measuring hedonic content response to customized content     |
| Comfort with data usage      |                         | Perceived acceptability of personal use of data              |
| Perceived data safety        |                         | Critical assessment of the beliefs on secure data handling   |
| Trust in the platform        |                         | Measuring implications of data management practices on trust |
| Privacy-based concerns       | Multiple-choice (multi) | Establish the prevailing causes of anxiety                   |
| Behavioral intention         | 5-point Likert scale    | Evaluate personalization potential usage of app              |
| Perceived usefulness         |                         | Test utility of customized offers.                           |

#### Data Collection Procedure and Analytical Model

The digital self-completed survey was employed to collect data, which made it widely available and minimized the risk of interviewer bias. The respondents were all volunteers and had to confirm that they had used one of the FDA previously to be considered relevant at an experiential level. The responses were filtered on the completeness criterion, and the partially filled questionnaires were filtered to maintain consistency in analysis.

The analytical plan had only used descriptive statistics because the purpose of the research was an exploratory and interpretative and not inferential. Frequency distributions, relative percentages and measures of central tendency were calculated in order to analyze the clustering of responses in Likert categories *i* as well as to establish an overall pattern of prevailing perceptions without any causal assumptions. To compute the relative frequency of response category *j*, we used Eq. (1),

$$p_{ij} = \frac{n_{ij}}{N} \tag{1}$$

in which *n<sub>ij</sub>* represents the number of valid responses, *N* is the sum of *n<sub>ij</sub>* denoting the number of people who chose item *i* in category *j*. In order to make items interpretable, agreement and disagreement tendencies were also formulated in terms of aggregated proportions, where it was defined respectively using Eq. (2).

$$A_i = \sum_{j=4}^5 p_{ij}, D_i = \sum_{j=1}^2 p_{ij} \tag{2}$$

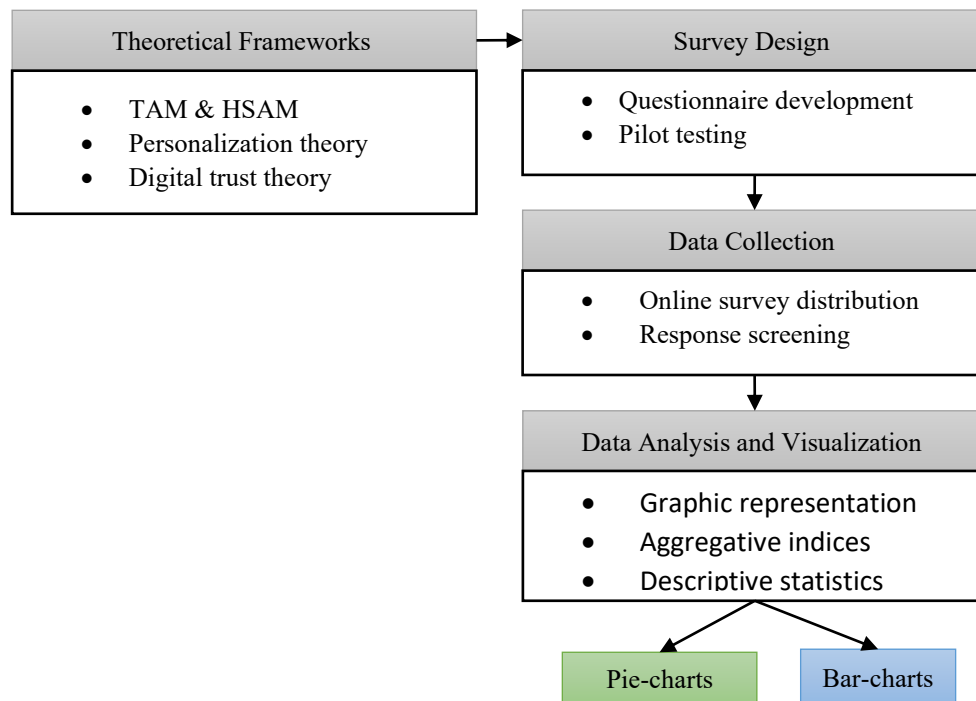
where  $A_i$  captures the overall agreement (agree and strongly agree) and  $D_i$  captures the overall disagreement (disagree and strongly disagree), but the midpoint value category was kept as an analytically distinct neutral measure. Notably, the items were subjected to the transformations in an identical way, so that the methodological consistency would be preserved, but the statistical dominance and confirmation of the hypotheses are not implied. In order to promote transparency and replicability, **Table 2** describes the main descriptive measures that were calculated on Likert-scale items in the analysis.

**Table 2.** Statistical Indicators Used in the Analysis

| Indicators                | Formula/Symbol              | Analytical Role                                       |
|---------------------------|-----------------------------|---|
| <b>Absolute frequency</b> | $n_{ij}$                    | Frequency of responses category                       |
| <b>Relative frequency</b> | $p_{ij} = \frac{n_{ij}}{N}$ | Makes it possible to compare proportionately          |
| <b>Agreement index</b>    | $A_i = \sum_{j=4}^5 p_{ij}$ | Caught positive attitudinal tendency                  |
| <b>Disagreement index</b> | $D_i = \sum_{j=1}^2 p_{ij}$ | Catches negative attitudinal tendency                 |
| <b>Neutral proportion</b> | $p_{i3}$                    | Determines the presence of ambivalence or uncertainty |

*Methodological Flow and Decision Logic*

The methodological procedure was created to support a logical and progressive thinking process that will increase consistency between theoretical ideas, measurement processes, and analytical findings. Originally, the questionnaire remained based on the theoretical, which were formulated based on the personalization and privacy literature; the questionnaire was then administered and the answers that were obtained were then filtered through filtering procedures to ensure validity.



**Fig 1.** Research Design Methodology Flowchart

Bar charts and pie charts were used to obtain descriptive statistics and to visually present distributional characteristics in order to convert Likert scale responses into quantitative data. This brought out more interpretive clarity as suggested in exploratory consumer research. The methodology decision logic was not supposed to accept or reject hypotheses, but rather to provide direction in the analysis path depending on the type of data. The responses in Likert scale instigated proportion-based, aggregation analysis, whereas the multiple-choice items underwent comparison of supplementary frequency using

categorization. Such a decision-oriented strategy made sure that every data structure received a proper analytical methodology to minimize the noise of methodologies and strengthen internal consistency.

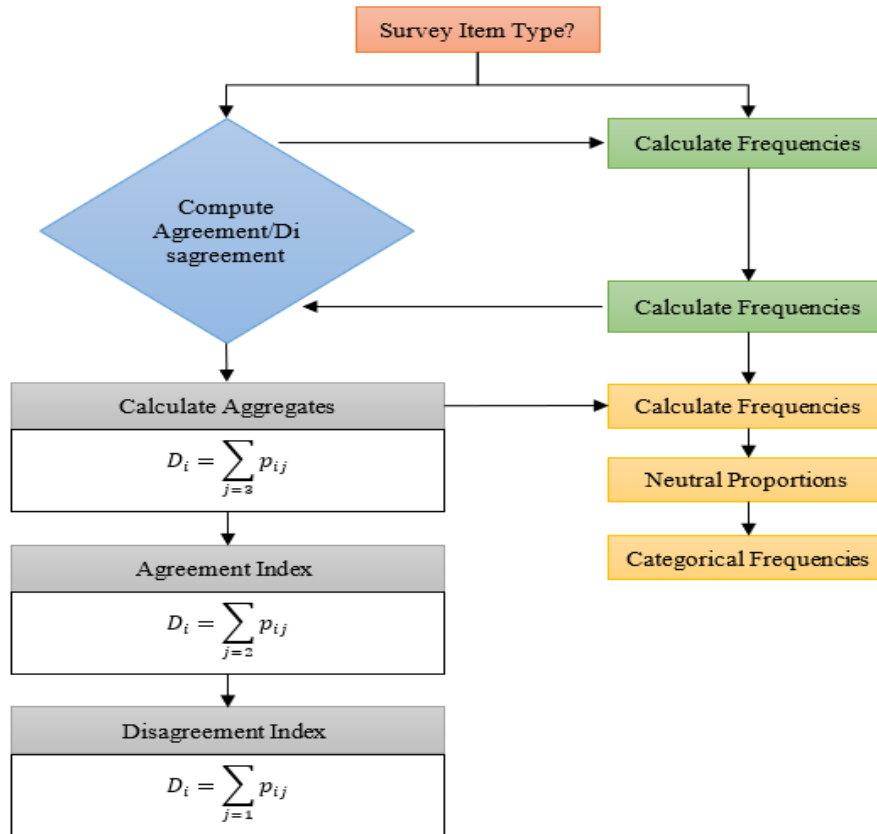


Fig 2. Selection of Analytical Procedure Decision Diagram

The general scheme of the methodological flow (including theoretical grounding and analytical output) is shown in Fig 1, whereas Fig 2 shows the decision diagram that could be applied to select the necessary descriptive procedure in accordance with the item type. Here both diagrams are directly mentioned to explain the logic of operation that lies behind the study and to make the methods more transparent to replicate and critically evaluate the study.

IV. RESULTS AND DISCUSSION

Comprehending how consumers view personalized advertisement content within the food delivery sector is fundamental. Every concern addressed in this section has been developed in reference to literature by Vasani, Rao, and Gupta [15] and Shyan, Verma, and Agarwal [16]. These works provide deeper understanding into respondent’s attitudes and perspectives towards confidential data usage to provide personalized advertisement content. Concern 1 is to evaluate the respondents’ enjoyment of customized content, particularly of customized offers and recommendations in FDA.

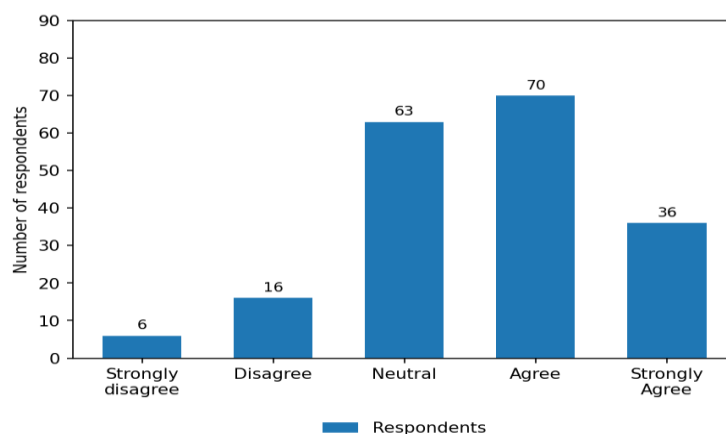
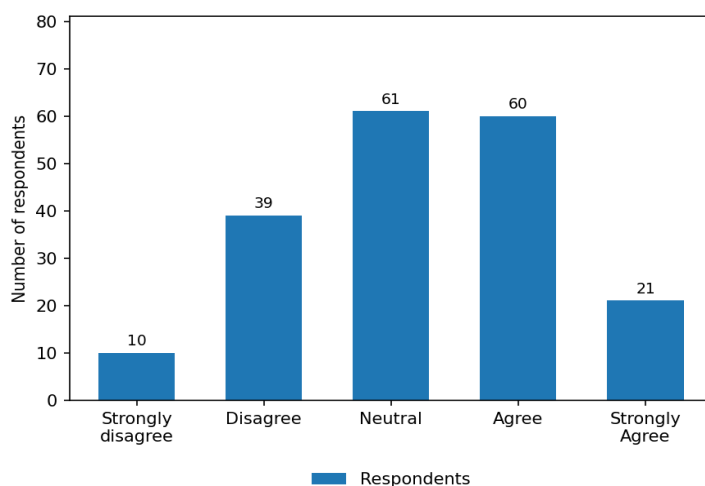


Fig 3. Addressing Concern 1, Enjoyment of Personalized Advertisement Content

As shown in **Fig 3**, participants have a tendency of finding personalized content pleasurable. In that regard, 36.01% of the respondents (70), and 18.81% (36) represented those who “agree” and “strongly agree”, respectively. Nonetheless, 33.01% (63), 8.42% (16), and 3.11% (6) of the respondents maintained a “neutral”, “disagree” and “strongly disagree” positions, respectively. Most of the participants, 55.41% (106), have good emotions/feelings according to feedback such as “strongly disagree” and “agree”, with a high selection of them settling on the “neutral” position, while a low portion settling on “strongly disagree” and “disagree” position (11.50%, 22). Personalized offers and recommendations are enjoyed and well-received by respondents.

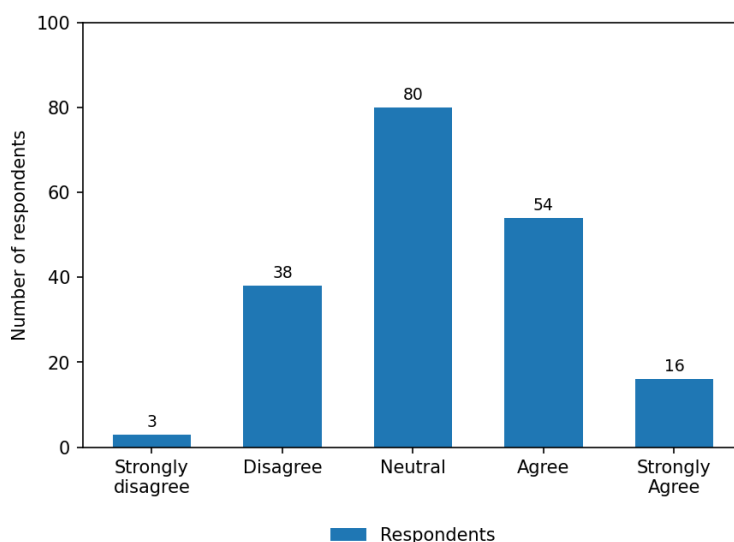
Most of the concerns focused on the usage of data in content produced by FDA. As illustrated in **Fig 3**, the overall predisposition is geared towards the agreement and neutrality element when it comes to acceptability of respondent-specific data employed by FDA. The “neutral” position represented 31.91% (61), whereas the “agree” position slightly reduced to 11.01% (60) from 31.40% (60) in the “strongly agree” position.

Approximately 5.22% (10) of the participants “strongly disagree” while 20.40% (39) “disagree”. The total number of participants who “strongly agree” and “agree” represent 42.43% (81), which surpasses the “neutrality” position with 31.91% (61) and those who “strongly disagree” and “disagree” jointly represented 25.61% (49). In general, while a significant portion of participants maintained a “neutral” position, **Fig 4** illustrates Concern 2, and highlights a high tendency to be “neutral” and “agree”, proposing that many respondents are willing to share and allow deploying personal data for customized content within the food delivery sector.



**Fig 4.** Addressing Concern 2, Willingness to Share Data and Receive Personalized Content

**Fig 4** shows that the highest feedback chosen is actually “neutral” representing approximately 41.82% (80), followed by “agree” and “disagree”, representing 28.31% (54) and 19.91% (38). As documented in **Fig 5**, the “strongly disagree” position tends to be the least chosen by participants, with just 1.60% (3), while “strongly agree” position represented 8.61% (16). These findings addressed Concern 3, which posit that FDA handle consumer data (i.e., location data) securely.



**Fig 5.** Addressing Concern 3, Apps Handle Personal Data Securely

During the computation of “strongly agree” and “agree”, we obtained a percentage total of 36.71% (70), which significantly lower compared to “neutral” position. The overall sum of “strongly disagree” and “disagree” represents 21.51% (54), which is lower than the “neutral” position percentage, as well as the summation of both “strongly agree” and “agree” positions. In response to our results, respondents tend to take the position of neutral more, regardless of how big the bigger choice is inclined to be in the direction of the agree position, in terms of evaluating the privacy with which user data is handled by the FDA in question.

However, in terms of the anxiety associated with the management of user data and its influence on the confidence in FDA, in compliance with Fig 5, this tendency is reversed. The findings showed that 32.51% (62), and 16.63% (26), represented “agree” and “strongly disagree” positions, which altogether represent 46.11% (88) of our study sample (see Fig 6). Unlike the previous results, both the “disagree” and “neutral” counts seem to have a low variation in the number of participants, which represented 22.50% (43), and 25.72% (49) of the participants. Respondents who “strongly disagree” represented approximately 5.81% (11), and if joined with those who “disagree”, the total count reached 28.33% (54). Our findings of Concern 4 illustrate that while a significant portion of participants represented those who “agree” highlighting that they believe that management of respondent-based data impacts their trust, a significant percentage remained skeptical or neutral by choosing either “disagree” or “neutral” positions.

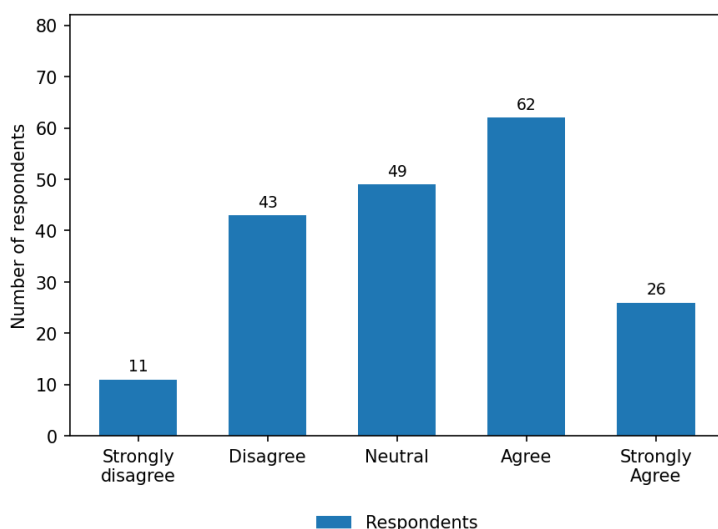


Fig 6. Addressing Concern 4, Management of Personal Data Impacts Trust

Concern 5 related more explicitly to the respondent’s views on the application of respondent-based data in advertisements from FDA. The three most frequently individualized are data misuse, privacy concerns, and third-party transactions that constitute 60.71% (116), 46.62% (89) and 39.92% (75) respectively. Finally, 15.71% of the respondents (30) claimed that they have no concerns, and 0.11% (2) was the individuals who are aware of how cyber security functions and that people know my address and whereabouts (see Fig 7, Concern 5). Our data have revealed that the largest concerns by users in regards to the handling of respondent-based data by these FDAs are third-party transactions, misuse of data and privacy and small percentage expressed no concerns.

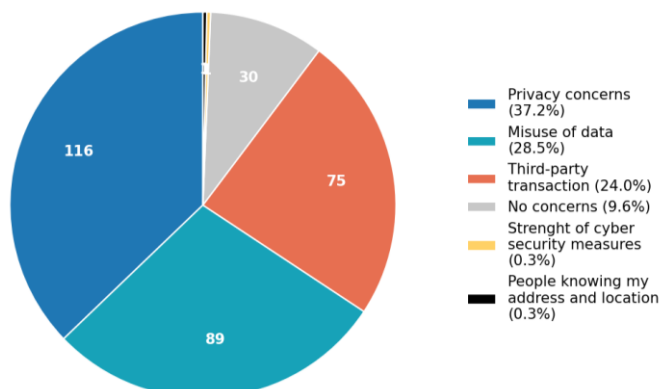


Fig 7. Addressing Concern 5, the Application of Data to Individualized Advertisement Content

Fig 7 shows that 32.51% (62) of the participants declared being “neutral” regarding the probability of using apps that provided customized content. By summing the proportions of both “agree”, and “strongly agree”, the overall number of

respondents, 35.61% (68), stimulated the application of FDA with individualized advertisement content. This number is slightly greater compared to sum of both “strongly agree” and “disagree”, representing 31.93% (61). Particularly, the percentage of participants selected the “agree” position represented 23.61% (45), while those who opted for “strongly agree” represented 12.01% (23).

Contrarily, the proportion of participants who “disagree” represented 20.41% (39), whereas the proportion of those who “strongly disagree” was 11.51% (22). These findings propose a slight reduction towards employing FDA that provide customized content. In fact, the summed proportions of both “strongly agree” and “agree” surpass the proportion of both “strongly disagree” and “disagree”, as well as those who opted for the “neutral” position.

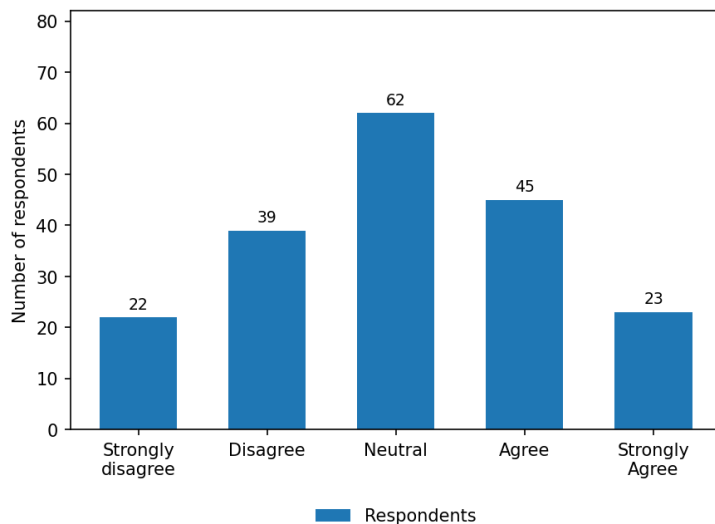


Fig 8. Addressing Concern 6, Using FDA Providing Customized Advertisement Content

The Likert scale in Fig 8 provided a significant variation between “agree” and “disagree”. Remarkably, the “agree” and “neutral” positions recorded a similar percentage of 31.80% (61), which shows a close connection between them. The final position, “strongly agree” represented 15.2% (29), which was significantly lower. Contrarily, 15.71% (30), and 5.21% (10) represented the lowest positions of “disagree” and “strongly disagree”, respectively. This level of distribution highlights a stronger pattern of those who “strongly agree”, and “agree”, since the summation of those who are in agreement is 47.11% (90). This proportion is more than 20.92% (40), and 31.92% (61), which represent those who “strongly disagree” and “agree”. In general, there is satisfactory option towards individualized advertisement content for an enhanced consumer experience.

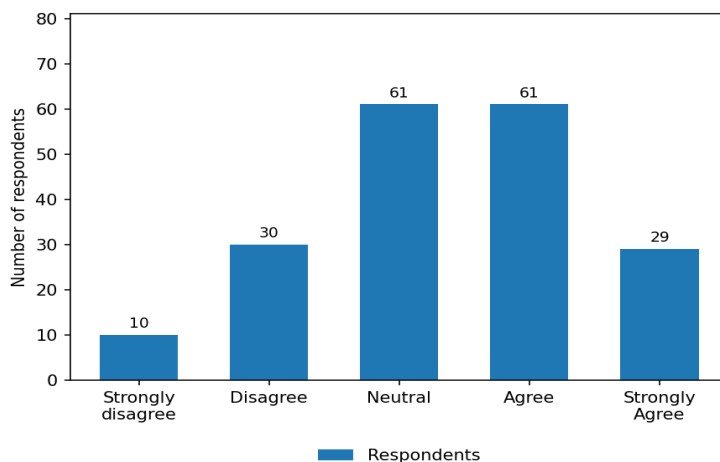


Fig 9. Addressing Concern 6, Individualized Advertisement Content Enhances the Overall User Experience

Concern 7 shifts to concentrating on respondents’ frequency to notice a typology of individualized advertisement content, as shown as Fig 9. Fig 10 highlight that most of the participants recorded a position of “sometimes” representing 42.41% (81), slightly more that the position of “often”, and “rarely”, which represent 35.62% (68), and 12.63% (24), respectively. The smaller proportions in Fig 10 represent an “always” and “never” positions representing 6.32% (12) and 3.12% (6), respectively. The results show a significant propensity among respondents to focus on customized recommendations, with most of them seeing this content regularly.

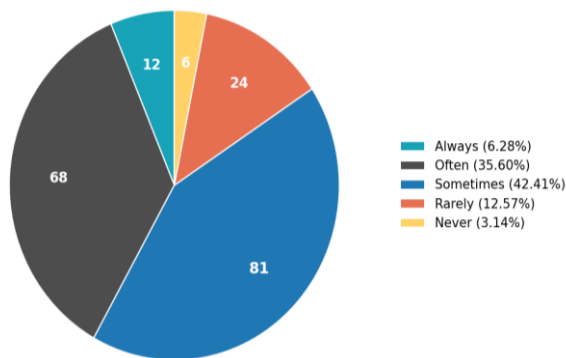


Fig 10. Addressing Concern 7, how Often Users Notice Individualized Recommendations

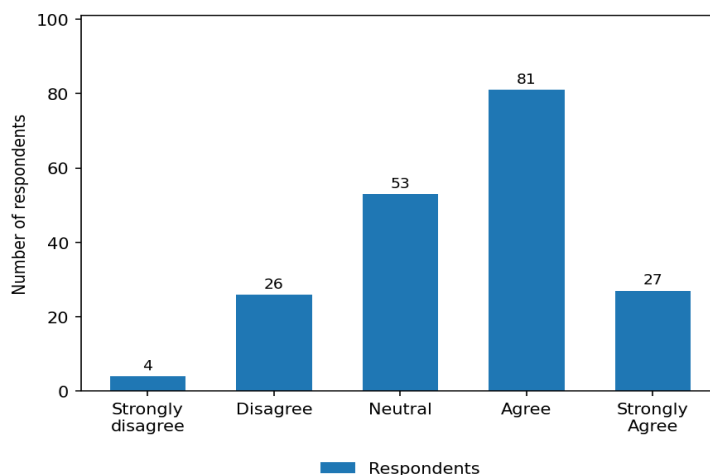


Fig 11. Concern 8, Individualized Recommendations are Useful and Relevant

In reference to Fig 10, users have transitioned from typically issues to how they perceive individualized advertisements in FDA. Fig 10 is based on 1 to 5 Likert scale, demonstrating a positive and notable inclination towards the concern. Distinct from the above, the greatest response rate focusses on the “agree” position, which represents approximately 42.42% (81).

Secondly, 27.73% of the respondents settled on a “neutral” position, while 14.12% (27) represented those who “strongly agree”. Those who “disagree” and “strongly disagree” represent 13.61% (26) and 2.11% (4), respectively, highlighting a stronger agreement that individualized advertisement content is both useful and relevant (see Fig 11). Lastly, by summing both “strongly agree” and “agree”, we obtain 56.51% (108), which is significantly more than those who “strongly disagree” and “disagree” i.e., 15.72% (30), including those who took a “neutral” position representing 27.71% (53).

### V. CONCLUSION

We provide an investigative disclosure about the consumers’ perception regarding individualized marketing content in FDA. Our descriptive results have shown that personalization has been perceived to be enjoyable, helpful, and can improve the overall user experience. Nonetheless, these favorable impressions coincide with a significant level of neutrality and anxiety regarding the personal data use, security, and access to them by a third-party. The perceived benefits of a service enhance trust, although it may also be decided by the degree of transparency and safety of processing users’ data. When there is a theoretical inclination of the behavioral intention towards personalized platforms albeit at a minimal level, reluctance is still evident to a high percentage of users. The results indicate that there is need to implement a balanced policy of personalization that emphasizes on privacy, data security and proper communication to build trust. FDAs can promote acceptance of the customized marketing approach and reduce the opposition to privacy-related concerns by ensuring transparency and user control.

#### CRedit Author Statement

The authors reviewed the results and approved the final version of the manuscript.

#### Data Availability

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

**Conflicts of Interests**

The authors declare no conflict of interest

**Funding**

No funding agency is associated with this research.

**Competing Interests**

There are no competing interests.

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