Investigating Privacy Decision-Making Processes Among Nigerian Men and Women

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ABSTRACT

The privacy calculus framework and trust heuristics has been used to understand people's privacy decision-making processes. However, most existing studies are mainly focused on people from developed countries. In this study, we use the privacy calculus in combination with trust heuristics to analyse how people from a developing African nation make decisions. Specifically, we conduct a web-based experiment in which 232 participants from Nigeria used a financial planning prototype app to respond to a number of disclosure questions. We examined how their perceived benefit, perceived sensitivity, and trust in the app influenced their disclosure decisions. In addition, we investigated possible moderating effects of gender and used Partial Least Squares path modelling to analyze our data. Our results show that perceived sensitivity (risks) and perceived benefits influenced the decision-making process of our participants. In addition, women were more likely to change their perception of sensitivity and benefits based on trust, while men were more likely to disclose information based on their perception of benefits. We also found that women were less likely to disclose their information to the app than men. Based on our findings, we make recommendations for educators, financial institutions, designers, and policymakers that aim to raise privacy awareness and design interventions in Nigeria and Africa at large.

KEYWORDS

Privacy Calculus, Trust Heuristics, Information Disclosure, Gender, Nigeria.

1 INTRODUCTION

Researchers are now looking at how culture and other societal elements affect privacy and privacy behaviour as a result of privacy's varying but ubiquitous nature. For example, Omrani and Soulié [53], focused on individuals' internet privacy concerns across different country groupings. Miltgen and Peyrat-Guillard [47] studied the personal data disclosure rate of European citizens, and showed a cultural and generational divide in privacy perception, concluding that there are clear divides between the south and east of Europe on the handling disclosure of information. Nonetheless, several scholars have pointed out that most existing studies about privacy behaviours focus on western countries, sometimes referred to as Western, Educated, Industrialized, Rich, and Democratic (WEIRD) [10, 77]. Very few studies are conducted on non-Western societies (Categorized as non-WEIRD countries) such as the African countries [41]. Moreover, the gender digital divide in technology tends to be higher in Africa [16] compared to WEIRD countries, where narratives around technology use and gender tend to focus on women's shortfalls and difficulties in keeping up with men. According to a study conducted in 2020 by the World Wide Web Foundation in Uganda, Ghana, Columbia and Indonesia, over 45 percent of women in these countries said they did not know how to use the internet [79]. Nigeria has a poor gender parity score of 0.55 (which indicates a high gender gap) [16]. A report from the central bank of Nigeria suggests that there is a wide gender disparity in favour of men in Nigeria especially in the areas of financial inclusion, education and technology [9]. The factors that contribute to this digital gender disparity in these countries are diverse, ranging from economic and educational disparities between men and women to cultural expectations and traditional gender roles, as well as policies that fail to address systemic inequities.

Furthermore, Kotze et al. [36] conducted a research in South Africa that found that Women are less willing to accept new technologies and show greater concerns about internet technology than men do. Indeed, researchers have questioned whether the internet can serve as an egalitarian medium given that less skilled users, who may be primarily women, may be unintentionally barred from the benefits of the internet due to their concerns about privacy [57]. In spite of the existence of a number of research in the area of gender and privacy [36, 57], further research is necessary to understand the privacy decision-making process of Nigerians, which is a non-WEIRD country.

The aim of this study is to fill the need to investigate how Nigerians make privacy decisions and whether men and women in Nigeria differ on how they make information disclosure decisions in the context of a financial planning application. This study investigates factors that impact the privacy decision-making process by combining the privacy calculus constructs of perceived sensitivity (a person's calculated perception that disclosing information will

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Proceedings on Privacy Enhancing Technologies 2023(1), 294–308
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https://doi.org/10.56553/popets-2023-0018

likely lead to a risky situation), and perceived benefit (a person's calculated perception that disclosing information will improve the recommendation quality i.e. advice on savings, spending behavior and investment provided by the app) [76], with trust heuristics (a person's intuitive belief that the app will serve the purpose which it claims [21]). This hybridized approach of combining the privacy calculus and trust heuristic frameworks provides deeper insights into what Nigerians consider when making privacy decisions. Furthermore, we discuss gender differences in privacy attitudes, perceptions and decisions. The recent proliferation of numerous fintech applications and loan apps in Nigeria served as a major motivation to the study. Additionally, this study aims to help app developers in Nigeria make better-informed decisions when designing information disclosure interfaces for financial planning apps and to further aid regulators propose regulations that will protect Nigerian users' privacy. We adopted the same study design as Anaraky et al. [21], who studied information disclosure in a similar context on a United States (US) audience. This allows us to make comparisons between the Nigerian and US contexts.

We conducted a study with 232 Nigerians using a prototype financial planning app and found that in employing the privacy calculus, participants considered the perceived quality of the recommendations (i.e., perceived benefits) but not the perceived sensitivity of the information (i.e., perceived risks) in making information disclosure decisions. These results are in contrast with Anaraky et al. [21], who find that US participants' disclosure to a financial app is influenced by the perceived sensitivity of the data, but not the perceived quality of the recommendations. Furthermore, in line with Anaraky et al. [21], we find that participants' trust in the app did not directly influence their information disclosure decisions, but rather trust influenced respondents' perception of the sensitivity of the information and the quality of the recommendation. In addition, we found attitudinal, perceptual, and behavioral differences between men and women. Notably, men disclosed more information than women, while women's perception of benefits (quality of the recommendations) was a significantly stronger factor in making disclosure decisions than for men. Furthermore, unlike men, women's perception of sensitivity was significantly influenced by trust. To summarize, our main contributions are twofold:

(1) We demonstrate that unlike US participants, Nigerians—and particularly Nigerian women—can be convinced to share their personal information if they are aware of the benefits of doing so. Nigerian women are also more likely to reduce their perception of the sensitivity of personal information if they trust the other party. These findings constitutes an important privacy consideration for a country with a growing information economy and a rapidly-increasing participation rate for women.
(2) At the same time, our results also demonstrate that unlike US consumers, Nigerians may not reduce their disclosure tendencies after learning about the potential risks of disclosing sensitive information. This suggests that African policy-makers must be careful to adopt US strategies to promote privacy-protective behaviors that emphasize disclosure risks. At the end of this paper, we discuss the implications of our findings for app designers, privacy researchers, and policymakers.

2 RELATED WORK

This section outlines related research on privacy decision-making, culture and privacy, and how gender differences in the effects of privacy exacerbate the digital divide.

2.1 Privacy Decision-Making: A Hybrid Approach

There has been much research into privacy decision-making across various domains [20, 35, 58]. Irrespective of the domain, several studies suggest that users employ a privacy calculus, i.e., they rationally make privacy decisions by trading off the benefits and risks associated with the decision [58]. For instance, users may have to consider the benefits of obtaining live directions from a navigation app versus the risks of their location data being obtained by the said app, or the benefits of a messaging app importing contacts from their mobile address book versus the risk that the app may use this list of contact information for advertising purposes [50, 66].

User's perception of information disclosure occurs because of competing influences of benefits and perception of risks when dealing with an unfamiliar e-commerce vendor. To demonstrate this, Li et al. [41] hypothesized and empirically examined how the privacy calculus constructs of risks and benefits influence an individual's decision to disclose information in an e-commerce context and found that privacy calculus constructs of risks and benefits influence disclosure decisions. Similarly, Krasnova et al. [37] studied information disclosure in social media by employing the privacy calculus framework. They assessed benefits by measuring the beneficial functions social media, such as relationship maintenance, enjoyment, and self-presentation. They used privacy concerns, the expected chance of various privacy violations, and the perceived damage of a possible violation to calculate the cost of disclosure. Overall, they showed that a high perceived benefit and low perceived risk will positively influence self-disclosure [37]. As demonstrated through these research publications, Scholars have employed a few methods to operationalize the costs and rewards that determine disclosure in the privacy calculus framework.

However, some studies argue that users may not make a rational trade-off between perceived costs and benefits because of the complicated nature of privacy decisions and humans' limited ability to obtain and analyze relevant data [2, 4]. Some scholars have shown that user's privacy decisions can be influenced by spurious heuristic factors, and may not be deliberate evaluative decisions of benefit and cost as the privacy calculus suggests [2, 67]. Acquisti et al. argue that this heuristic view of online sharing behaviours does not mean that people are careless in making privacy decisions; rather, users are concerned about online privacy, as demonstrated by the numerous actions they take to protect it. However, they show how difficult it is to achieve desired, or even desirable, levels of privacy through individual actions [3]. Similarly, Sundar et al., in their work, argue that disclosure decisions are not always made rationally as these decisions may occur due to the necessity in the heat of the moment. They argued that cognitive heuristics would be used to make disclosure decisions when there is limited information and necessary to make a decision [67]. Presentation and framing are factors that could influence privacy decision-making; for example, Johnson et al. investigated how framing and default settings influence users' privacy decisions [33]. They found that users are more likely to accept a pre-selected privacy option or make disclosure decisions when presented with a positive framing. Marmion et al. argued that relying on cognitive heuristics is the key to explaining privacy decision-making. They used an existing credibility framework to access users' disclosure decisions. Users rely on six super-ordinate kinds of heuristics during disclosure. They concluded by suggesting that proactively nudging users through the indicators that emphasize these simple heuristics could be the key to assisting them throughout disclosure decisions [45]. These studies of heuristics show that users' privacy decisions often rely on unclear and heuristic processes that may seem irrational when studying users' privacy disclosure decisions.

Dinev et al. [11] examined the willingness to disclose information to complete transactions on the internet. Futhemore, Dinev et al. [11] discovered that, while perceived privacy risks and concerns hinder disclosure (the costs of privacy calculation), users' trust in the internet and personal interests can supersede these costs and influence data disclosure decisions. Some scholars have recently found that combining the privacy calculus with heuristics will give a clearer picture of the user's disclosure decisions. For instance, Wang et al. [76] integrated the privacy calculus model and elaboration likelihood theory to reconcile privacy decision-making's rational and heuristic views. While the privacy calculus decision-making process held true in general, they discovered that peripheral cues and information asymmetry worked as heuristic elements that influenced users' disclosure decisions.

Anaraky et al. [21] employed a hybrid method to explore privacy decision-making. Using privacy calculus and trust heuristics, they used a web-based application to examine the privacy decision-making processes of older and younger people. They investigated how app trust, data sensitivity, and disclosure benefits affected users' disclosure decisions and found that older adults made more rational decisions than younger adults, who made heuristic decisions based on app trust [21]. For this study, we adopt the approach of Anaraky et al. to investigate the privacy decision-making process of Nigerian men and women. This allows us to make comparisons between the Nigerian and US contexts.

2.2 Culture and Privacy

Scholars have demonstrated that culture has a substantial influence on people's privacy perceptions and behaviors. For example, Miltgen and Peyrat-Guillard [47] examined the personal data disclosure rate of European citizens based on geopolitical locations. They showed the existence of a cultural and generational divide in privacy perceptions and concluded that there are clear divides between the south and east of Europe on how they handle the disclosure of information. Trepte et al. [47] report that people from cultures ranking high in individualism found it less important to generate social gratifications on social networking sites (SNSs) compared to people from collectivist-oriented countries and that collectivist-oriented European countries placed more emphasis on privacy risks.

Li et al., [42] developed a cross-cultural privacy prediction model that incorporates cultural, demographic, attitudinal, and contextual factors. They suggest that when examining the determinants of information privacy concerns or defining privacy-related policies, participants' cultural backgrounds should be taken into account.

Additionally, the effect of culture on privacy can also be found with different cultures within a country. For example, a study conducted in the United States showed that privacy behaviour varies across people of different cultures as 35 percent of Asian Americans, African Americans, and Hispanic Americans, but only 21 percent of White Americans, never managed their SNS privacy settings [13]. Viseu et al. suggested that place and culture are important factors to consider in privacy practices [74]. Hence, culture is an essential issue to consider when analyzing privacy behaviour. An important consideration for cross-cultural privacy research is the definition (and, subsequently, the measurement) of culture.

Daffalla et al. [10] reinforced that there exist privacy behaviour differences amongst cultures and countries, they opined that users from non-WEIRD (Western, Educated, Industrialized, Rich, Democratic) populations may have overlapping similarities with vulnerable populations. They emphasised that vulnerable populations have a variety of needs that may or may not be met by standard security assumptions made by developers, and they encouraged researchers to study a variety of populations around the world in order to uncover additional key factors such as design principles, technology usage, and its impact on non-WEIRD and vulnerable populations [10]. To bridge this gap, Our research focus region for this study is Nigeria which is a non-WEIRD society, This extends the important line of research on a hybrid approach to privacy decision-making beyond individualist societies (i.e., Anaraky et al. [21] and Markos et al. [44] sampled from the United States and Trepte et al. [72] from Europe). We examine the privacy decision-making processes of Nigerians, as it is possible that privacy decision-making may incur cultural differences, considering that different cultures seem to disagree regarding what is considered private [41].

2.3 Gender and the Digital Divide

In addition to culture and age, gender is another demographic factor that has been studied in the context of privacy. Some studies on the effect of gender on privacy found that there is a sizable effect of gender on privacy behaviour and that the gender disparities reliably manifest in favour of men in the privacy protection that involves technicality [57, 78]. Another study compared self-disclosure among men and women with different dispositions to trust. Women with low trust disclosed substantially more information about themselves than men with low trust. In addition, women with high trust revealed much more personal information than men with high trust [19]. Arguably, gender differences in privacy and disclosure are exacerbated by the gender-based digital divide (inequalities in Internet access, use, knowledge of search methods, technical connection quality and skills, social support, discerning of information quality, and variety of uses) that is particularly prominent in Africa [29, 36, 57, 79]. According to Weinberger et al. [78], there is a digital divide between men and women regarding technical knowledge and the skills used to protect their personal information on the internet. Women's online privacy self-efficacy and knowledge of technology risks are higher than men's, but their technological online privacy literacy is lower. Other researchers have found that women are more concerned about their privacy than men [61, 70]. Understanding how economically or socially constructed gender differences influences privacy decision-making can help identify factors to consider when developing technologies or enacting legislation that protects privacy. Therefore, our study seeks to investigate the possible moderating effect of gender in privacy decision-making.

3 RESEARCH QUESTIONS AND HYPOTHESIS

In the sections below, we introduce our research questions and our research framework, which combines the antecedents to privacy decisions as envisioned by the privacy calculus theory (i.e., perceptions of benefits and costs) with antecedents that may indicate the use of heuristic processes (i.e., trust in the app) to understand users' information disclosure decisions. This section also addresses the moderating effect of gender on disclosure.

3.1 Research Questions

Our research questions are motivated by gaps in existing research. First of all, despite the increasing research in users' privacy concerns, scholars have pointed out that most of the existing literature focuses on individualist Western cultures while neglecting privacy concerns in non-Western cultures [10, 44, 47]. As such, we apply the privacy calculus perspective to the Nigerian context and formulate the following research questions:

RQ1: *How do perceived benefits and costs of disclosure (perceived sensitivity) influence information disclosure decisions among Nigerians?*

Furthermore, gender differences have been neglected by many researchers [21]. We therefore investigate gender differences in the decision-making process:

RQ2: *Do adult women differ from men in terms of how they make decisions to disclose personal information online?*

Finally, we acknowledge that gender differences in privacy decision-making may not only manifest in a difference in approach, but also in a difference in outcome. Hence, we study gender differences in overall disclosure levels and formulated a third research question

RQ3: *Do adult women disclose more personal information online than adult men?* These research questions are further developed into hypotheses below.

3.2 Privacy Calculus: Perceived Benefits vs. Costs of Disclosure

The privacy calculus is a well-known theory that describes how people make information disclosure decisions by evaluating the advantages and disadvantages of disclosing the requested personal information [38, 76]. Nevertheless, different studies have utilized different methods to measure these elements of the decision-making process. To achieve our aim, we asked participants to reveal or withhold a variety of pieces of information to our financial app "Wedeliver", under the pretense that this information would be used to personalize the financial advice given by the app. Available literature has sought to address the relationships between personalization and disclosure decisions [5, 49]. In our study, we therefore operationalized perceived benefit as the perception that the requested information would improve the quality of the application's recommendations (in short: "anticipated recommendation quality"). We operationalized perceived cost as the perception that the requested information is sensitive (in short: "perceived sensitivity"). Previous research has linked perceived data sensitivity to increased disclosure risks, privacy concerns, and reduced information disclosure [44, 50]. In accordance with the privacy calculus theory, the anticipated recommendation quality and perceived sensitivity are our two independent variables (IV) predicting the dependent variable (DV)—the information disclosure decision:

H1: Anticipated recommendation quality will be positively associated with information disclosure.

H2: Perceived sensitivity will be negatively associated with information disclosure.

3.3 Trust as a Predictor of Disclosure

Trust is described as a person's expectations, assumptions, or thoughts about the likelihood that another future actions would be good, favourable, or at the very least not harmful to one's interests [60]. Some researchers believe that trust is primarily a psychological condition of perceived vulnerability or risk caused by people's uncertainty about the motives, intentions, and future behaviour of those they trust. Trust is closely related to privacy, as it enables us to share vulnerable aspects of ourselves with others while also getting to know them intimately [63]. Some researchers look at trust as a heuristic (a short-term cognitive process) that can speed up the disclosure decision-making process by replacing a calculative judgment regarding the requested information (e.g., in our study, the perception that the requested information would improve the quality of the application's recommendations, versus the perception that the requested information is sensitive) with an intuitive judgment regarding the requester of the information [30]. Zimmer et al. [80] established that the level of trust in an entity can affect the decision to disclose or not to disclose one's personal information [80]. The level of trust one has in an entity may vary based on experiences or other societal factors; for example, a Washington Post report suggests that there is a high distrust in government in many African countries [23]. A study conducted in Nigeria showed that Nigerians find it difficult to trust technology infrastructures, especially in the e-commerce domain [52]. In the context of our study, trust is defined as participants' trust in how Wedeliver (the app) manages and uses their personal information (in short: "app trust"). App trust is the third independent variable in this study, and we hypothesize both a direct effect and two mediated effects of trust on information disclosure:

H3: App trust will be positively associated with information disclosure.

H4: App trust will be positively associated with anticipated recommendation quality.

H5: App trust will be negatively associated with perceived sensitivity.

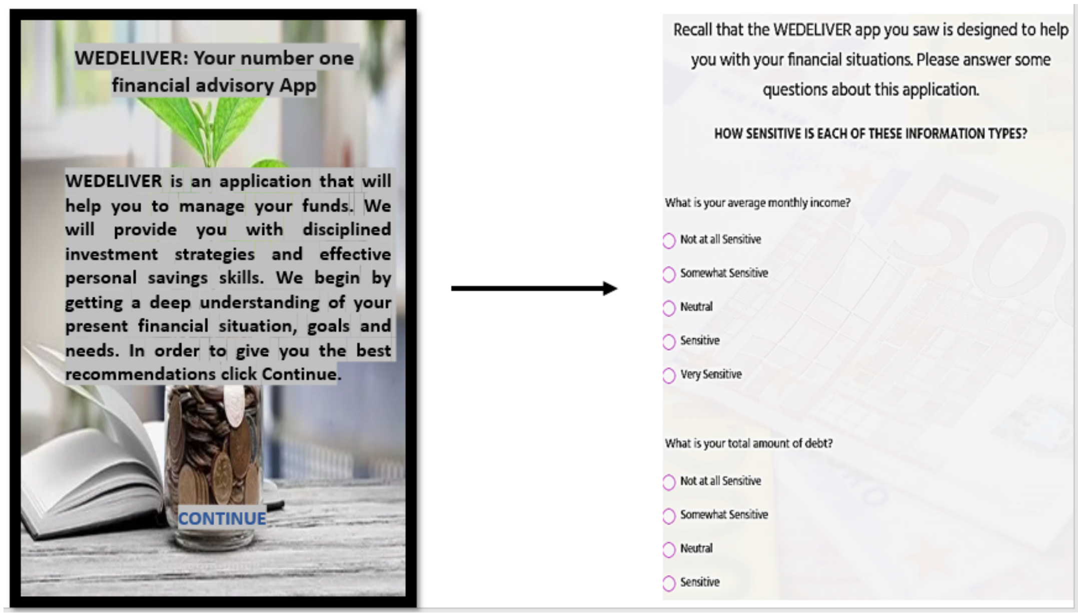

Figure 1: The experimental setup. After interacting with the app, participants were directed to a survey.

3.4 Gender Influences on Disclosure.

Particularly in Africa (but also in other regions), there has been a pronounced digital divide between men and women in terms of technical abilities to use the internet. According to a survey, over 60% of women in Northern Nigeria are unable to use the internet, and deeply rooted social, gender, and cultural norms constitute a significant hindrance to women's and girls' access to and use of information technology [15]. Several researchers have investigated gender inequalities in privacy. For example, Weinberger et al. [78] discovered that while there is a digital gap between men and women in terms of their technological ability to protect their privacy on the web, this did not result in a greater proclivity for men to engage in privacy protection behaviour than women. These findings are in contrast with the earlier research of Fogel and Nehmad [18], who found that women with high trust engaged in significantly more self-disclosure than men with high trust, and that low trust in women also translated to more self-disclosure when compared to men with low trust. They compared trust with self-disclosure and discovered that low trust in women translated to more self-disclosure when compared to men with low trust [18]. We argue that these contrasting findings may be the result of a dual difference between men and women: one in terms of privacy decision-making practices, and another in terms of overall disclosure. We therefore propose the following hypothesis:

H6:Nigerian Men and women will differ in their privacy decision making process, resulting in differences in the effects of anticipated recommendation quality on disclosure (H6a), of perceived sensitivity on disclosure (H6b), of app trust on disclosure (H6c), and of app trust on recommendation quality (H6d) and sensitivity (H6e).

H7: Nigerian Women will significantly disclose more information online than Nigerian men.

Table 1: Showing the Demographic Information of Participants

	Total of 232 Participants
Age	18-24: 27.20% 25-34: 49.60% 35-44: 18.50% 45 and above: 4.70%
Education	High School: 11.64% Bachelor: 53.02% Diploma: 12.93% Masters and above: 22.41%
Gender	Men: 50.88% Women: 49.12%

Our statistical approach (PLS-SEM, see Section 4.2) allows us to test these hypotheses as a single model consisting of a series of hypothesized relationships between variables (see Figure 2).

4 METHODOLOGY

In the sections below, we highlight the study overview, participants' recruitment, and the sample demographics. This section also outlines the validation of our measured constructs.

4.1 Study Overview

We acquired ethical approval regarding relevant regulations and compliance from the Federal University of Technology, Minna before collecting data. To achieve our goal, we designed "Wedeliver", a web-based prototype of a mobile app that can help users plan their investments and financial budgets. We recruited 232 participants to interact with the prototype. Participation in the study was conditional upon the participant reading the study description and giving their consent. The description informed participants beforehand that the app is solely for research purposes and will not make financial recommendations after answering the disclosure questions on the prototype app. The study therefore relied on participants' suspension of disbelief—a necessary limitation to avoid an unethical study design. While the frontend of the prototype app asked for sensitive information, the backend only stored whether the question was answered or the participant selected "I prefer not to say" (i.e., the actual answer to the question was not stored regardless), thereby avoiding potential security issues due to data breaches. Furthermore, participants were informed in the study description that there was not any form of reward for participating in the study, conducting studies without compensating the participants is common practice at Nigerian universities due to limited available funds.

After logging in, participants were led to a screen that discusses the app and how it works, shown in figure 1. To use the financial planning application, we asked participants to disclose a variety of personal data (e.g., bank account balances, annual income, and debts shown in Appendix section 1) with the ostensive goal of personalizing their financial advice. Participants had the explicit option to decline to provide any particular piece of information by choosing "I prefer not to say." Note that while the front-end of the "Wedeliver" prototype app asked for personal information, the backend only stored whether the question was answered or the "I prefer not to say" option was selected. This binary behavior (disclose vs. not disclose) is turned into a latent construct (see hypothesized model shown in Figure 2) that is considered as the main dependent variable of our study. We used binary variables to measure the data item of disclosure decisions (coded as 1 for disclosure and 0 for non-disclosure). After making Ten (10) disclosure decisions shown in table Appendix section 1, we invited participants to evaluate their trust in the app, the perceived sensitivity of each requested data item, and the anticipated effect of disclosing each item on the app's recommendation quality. Trust is measured using a 5-item pre-validated construct, while recommendation quality and sensitivity are assessed on a 5-point agreement scale (1 = strongly disagree to 5 = strongly disagree) for each of the 10 requested personal information items shown in Appendix section 3, section 4 and section 5. This scales are just as used by Anaraky et al.'s study [21].

4.2 Sample Demographics

The call to participate in the study was distributed through various social media platforms in 2021. Participants were recruited through posts on Facebook groups, pages, WhatsApp groups and direct messaging. Because we used snowball sampling, most participants did not have a direct relationship with the researchers. The recruitment link was shared by directly messaging friends and colleagues and asking them to share to their Whatsapp status, Whatsapp groups Facebook stories and Facebook groups. A total of 268 responses were received. We accepted and analyzed 232 complete responses from Nigerian adults which were deemed suitable after applying the following criteria:

- Responses must be provided for all questions
- Participants are from Nigeria
- Participants should be at least 18 years and over

Table 1 summarizes participants' demographic information. None of our participants identified as transgender or non-binary although there was an option to specify as one; this might be due to the precarious position and stringent laws against LGBTQ+ people in Nigeria [71] (i.e. participants who identify as such likely feel uncomfortable disclosing it as it may attract societal backlash).

4.3 Measurement Model

The survey constructs were adapted from existing research studies. For example, the disclosure questions, perceived sensitivity, app trust, and recommendation quality were adapted from Anaraky et al.'s study on privacy decision making and then modified to suit the current study context [21]. Specifically, we eliminated "credit scores", 'tax returns', and groceries from our disclosure questions as these terms are not generally familiar in Nigeria and may confuse the participants. We also modified the trust scale by adding the item 'I believe Wedeliver tells the truth and will use the information I provide to improve services for me'. We added this to the trust item as it directly relates to the major services the 'Wedeliver' app claim to offer. The participant recruitment was quite different from that Anaraky et al's study, we employed snowball sampling where individuals selected to be studied recruit new participants by sharing the study recruitment among their circle of contacts. The 'Wedeliver' prototype web application was designed to have surface credibility as it had competent look and feel and was hosted as a website.

4.3.1 Measurement Validation. To validate our measurements, we determined the suitability of our data for further analysis using the Kaiser-Meyer-Olkin (KMO) sampling adequacies and the Bartlett Test of Sphericity. Before using a data reduction approach, the Bartlett Test of Sphericity is frequently used to check for redundancy among the variables that we can summarise with a small number of factors. Our results showed that the KMO was 0.869, well above the recommended value of 0.6. The Bartlett Test of Sphericity was statistically significant $X^2(276) = 3159.403, p < 0.0001$. These results show that our data is suitable for further analysis [54]. We chose the Partial Least Square structural equation modelling (PLS-SEM) technique to analyze our data and develop models to test the research framework and hypothesis. PLS is a prediction-oriented approach to SEM. We chose PLS over other approaches (e.g., covariant-based) because it is highly appropriate for complex predictive models [39] and presents a flexible and robust feature in a user-friendly interface. The PLS Structural Equation Modelling is a powerful tool for showing the breakdown of the relationships between factors in an experiment. The PLS-SEM has been successfully used in estimating relationships between variables by many HCI and User Modeling researchers [7, 12, 54, 55].

We employed Partial Least Square structural equation modelling (PLS-SEM) technique to validate the measurement model [54]. We used the SmartPLS tool [59] to create the PLS-SEM models. The binary scale (disclose vs. not disclose) is turned into a latent construct

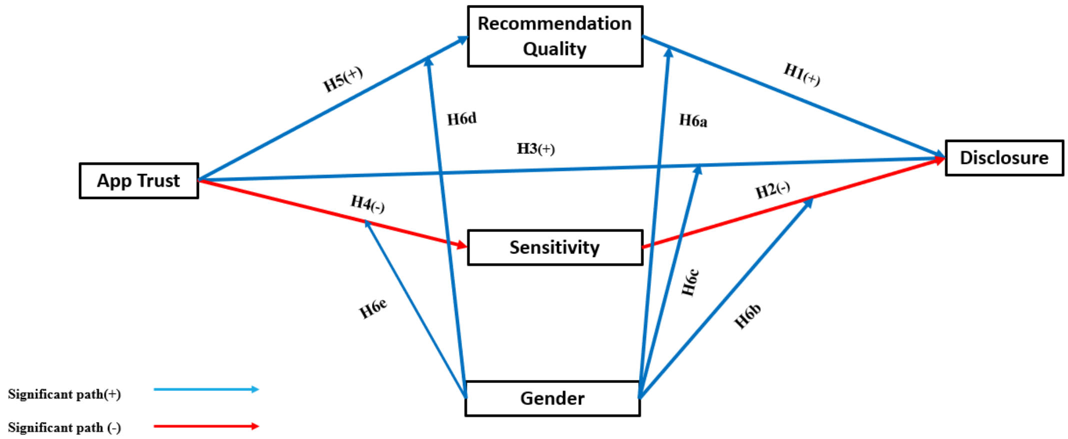

Figure 2: The Hypothesized Model

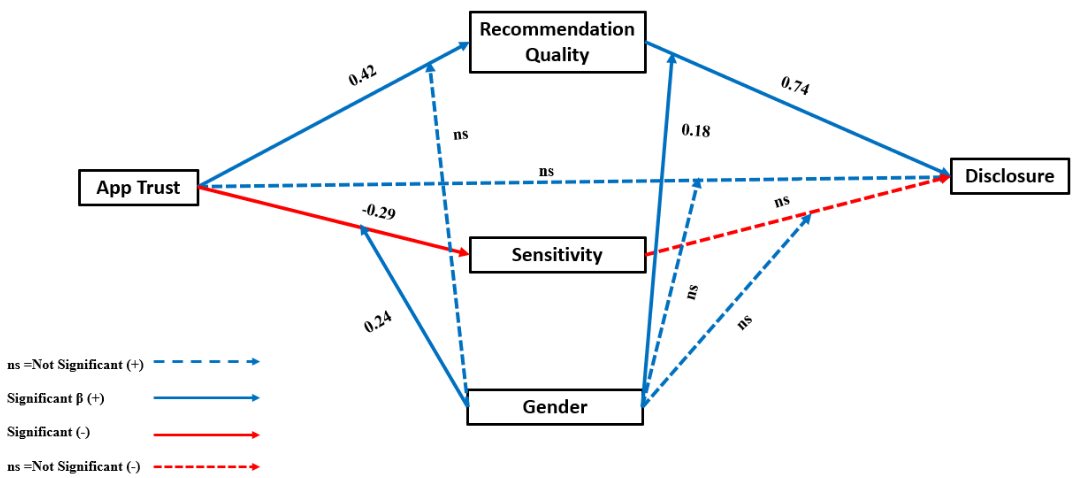

Figure 3: The path model including all of the significant findings.

(see hypothesized model shown in Figure 2). Also, the 5-point Likert scale (Recommendation Quality and app trust) was weighted as 5 for "strongly agree" to 1 for "strongly disagree" and "very sensitive" as 5 and "not at all sensitive" as 1. Answers to questions under each construct were used as indicator items and loaded directly on their corresponding latent variables. The PLS-SEM uses a latent variable approach, avoiding the need to sum or average the measurement items per construct. The items otherwise called indicators that made up each of the constructs were examined to ensure their factor loadings were above 0.40 (see Table 2) [46]. To establish the reliability of the model's constructs, we used cronbach alpha and composite reliability [65]. As shown in Table 3, all cronbach's Alpha values were above 0.70, which implies an excellent internal consistency of the constructs for perceived recommendation quality, Perceived sensitivity, App trust, and disclosure [68]. The composite reliability of the constructs also had values higher than the recommended threshold of 0.70 [27], Finally, the average variance extracted was above the recommended value of 0.5 for each factor, which indicates a good convergent validity [1]. The result shown in the Table 3 suggests that the model has good internal consistency, reliability, and validity.

The aim of the discriminant validity evaluation is to establish that a reflective construct has the strongest relationships with its own indicators [40]. We used the Heterotrait-Monotrait (HTMT) correlation ratio [27] to ensure discriminant validity. Henseler et al. [27] suggested that the HTMT attain higher specificity and sensitivity over the Fornell-larker and cross-loadings criterion. As HTMT values increase towards 1, the discriminant validity reduces. When using the HTMT criterion for discriminant validity, comparing the HTMT values to a predefined threshold is suggested. The value of the HTMT is compared to the threshold value and must be less than the threshold value to ensure discriminant validity. The acceptable threshold value is 0.90 [22]. As shown in Table 4, all the HTMT values are below the threshold value, which implies a good discriminant validity.

Table 2: PLS-SEM factor loadings of our questionnaire items on the 4 measured constructs.

Constuct	Item	Loadings
Disclosure	DIS4	0.563
Disclosure	DIS5	0.706
Disclosure	DIS7	0.740
Disclosure	DIS8	0.746
Disclosure	DIS9	0.818
Disclosure	DIS10	0.684
Recommendation	REC2	0.527
Recommendation	REC3	0.870
Recommendation	REC4	0.442
Recommendation	REC5	0.876
Recommendation	REC7	0.817
Recommendation	REC9	0.914
Recommendation	REC10	0.614
Sensitivity	SEN4	0.611
Sensitivity	SEN5	0.786
Sensitivity	SEN6	0.694
Sensitivity	SEN7	0.810
Sensitivity	SEN9	0.605
Sensitivity	SEN10	0.807
Trust	TRU2	0.791
Trust	TRU3	0.856
Trust	TRU4	0.840
Trust	TRU5	0.812

Table 3: Reliability statistics for the four measured constructs. All reliability statistics meet established acceptability thresholds. DIS= Disclosure, REC= Recommendation quality, SEN= Sensitivity, TRU= Trust

	Cronbach Alpha	Composite Reliability	Average Variance Extracted
DIS	0.81	0.86	0.51
REC	0.85	0.89	0.55
SEN	0.82	0.87	0.53
TRU	0.85	0.90	0.68

Table 4: Heterotrait-Monotrait correlation ratios for the four measured constructs. All values meet established thresholds for discriminant validity. DIS = Disclosure, REC = Recommendation Quality, SEN =Sensitivity, TRU=Trust.

Item	DIS	REC	SEN	TRU
DIS				
REC	0.89			
SEN	0.50	0.57		
TRU	0.38	0.50	0.32	

5 RESULTS

Because our data exhibited good construct validity and reliability, we kept all the constructs and conducted the final path modelling using PLS-SEM to develop a structural model showing the relations between the dependent variable (DV) information disclosure and independent variables (IV) perceived sensitivity, anticipated recommendation quality, and app trust (see Figure 2). The resulting model test can be compared to running several connected t-tests and regressions in a single model. PLS-SEM uses a latent variable approach: it avoids the need to turn measured constructs into sum scores or averages. All measured constructs are presented as standardized latent variables. The statistical results presented below have the same characteristics as standardized β-coefficients in a linear regression model (or Cohen's d, for between-group comparisons).

5.1 The Structural Model

The structural models determine the relationship between the recommendation quality, sensitivity, trust, and information disclosure (see Figure 3). For each effect, we report the path coefficient (β), and the statistical significance of the path coefficient (p-value) [24]. To test our hypothesized model, we used a 5000-subsample bootstrapped significance test.

First, we discuss the main effects of the privacy calculus and trust heuristics on information disclosure, and then we use a multi-group analysis that establishes two parallel models for men and women and makes pairwise comparisons to establish whether there are significant differences between the models for different gender groups with respect to their β values [28, 62].

5.2 Anticipated Recommendation Quality and Perceived Sensitivity (H1-H2)

H1 states that anticipated recommendation quality is positively associated with disclosure. This hypothesis was strongly supported ($p < 0.001, \beta = 0.74$), see Table 5, this implies that participant's perceived benefit would increase their likelihood to disclose information. However, H2, which states that perceived sensitivity is negatively associated with disclosure was not supported, hence perceived sensitivity for participants did not really affect the decision to disclose information ($p = 0.62, \beta = -0.03$).

5.3 App Trust (H3-H5)

H3, which hypothesized that App trust is positively associated with disclosure, was not supported ($p = 0.94, \beta = 0.004$). This implies that participants trust in the app did not directly influence their disclosure decisions. H4 hypothesized that there would be a positive effect of app trust on anticipated recommendation quality. We found support for this hypothesis ($p < 0.001, \beta = 0.42$), hence trust in the app was most likely to affect participants perceived recommendation quality. Furthermore, in line with H5, we found a significant negative relationship between perceived sensitivity and app trust ($p = 0.001, \beta = -0.29$), which may imply that participants who trust the app more would most likely have lower perceived sensitivity. Combining the effects of H1 and H4, and noting the absence of a direct effect of app trust on disclosure (H3), it seems

Table 5: Result for our hypothesized model showing path coefficient β and corresponding p-values. DIS = Disclosure, REC = Recommendation Quality, SEN = Sensitivity, TRU= Trust.

Item	Path Coefficient β	p Values
REC -> DIS (H1)	0.74	**< 0.001**
SEN -> DIS (H2)	-0.03	0.62
TRU -> DIS (H3)	-0.01	0.94
TRU -> REC (H4)	0.42	**< 0.001**
TRU -> SEN (H5)	-0.29	**< 0.001**

that the effect of app trust on disclosure behavior is fully mediated by anticipated recommendation quality.

5.4 The Moderating Effects of Gender

To test the moderating effect of gender (H6), we establish two parallel models for men and women, and compare the differences in path coefficients between these models to see which are statistically significant using the standard pairwise approach to multi-group comparison in SmartPLS. The first two columns present the regression coefficients β and significance (p-value) for men and women separately, while the final two columns present the interaction effect (i.e., the difference between men and women) and its significance. Our results show that men and women are significantly different in the extent to which anticipated recommendation quality influenced their disclosure decisions (H6a $p < 0.05$; see the bolded in Table 6). This effect is significant for both men and women, but it is stronger for women than for men. Moreover, men and women differ significantly in the effect of trust on perceived sensitivity (H6e $p < 0.05$); women's perception of sensitivity was significantly influenced by trust, but this effect is not significant for men.

To address H7, we conducted an independent sample t-test to compare the disclosure rate for men and women. The results show a significant difference ($t(217.022) = 5.262$, $p = < 0.001$). The mean score for men (M = 6.05 and Std. Dev = 2.26) is higher than that of women (M = 4.29 and Std. Dev = 2.80), suggesting that men have higher disclosure rates compared to women. This contradicts H7.

6 DISCUSSION

In this paper, we studied Nigerian adults' privacy decision-making, using a hybrid approach combining privacy calculus with trust heuristics. Additionally, we investigated whether men and women differ in how they make disclosure decisions about their personal information, and whether women have a higher disclosure rate than men. Our results showed that participants' perceptions of the benefits of disclosure (but, interestingly, not their perceptions of the cost of disclosure) influenced their disclosure decisions. This effect, however, was stronger for women than for men, such that the benefits of disclosure proved to predict disclosure better for women. Trust heuristics did not directly influence the privacy decision-making process. Instead, we found that participants (most prominently, women) use trust in the app to determine their perception of sensitivity and benefits. It is important to note that below, we offer our interpretations of the results and derive insights for privacy decision-making based on two propositions: (1) privacy calculus vs trust heuristics, and (2) gender and the digital divide. The result obtained from this study was then compared with a similar study carried out in the United States.

6.1 Privacy Calculus Vs Trust Heuristics Among our Nigerian Participants

Our results indicate that both privacy calculus and trust heuristic are complementary in comprehending users' privacy decisions. Our research model explains why a hybrid decision-making strategy incorporating privacy calculus and heuristic considerations is important when studying privacy disclosures. If we solely use privacy calculus or trust heuristic-based privacy decision-making models, neither technique would adequately represent the decision-making process of all of the population.

Disregarding trust in disclosure decision may be a byproduct of previous experiences. Many Nigerian netizens, regardless of gender, have suffered cyber-attacks and other forms of online security issues. According to a report from the Federal Bureau of Investigation Internet Crime Complaint Center, Nigeria was rated 16th in the world in countries most affected by cybercrime in 2020 [17]. Although there are different cybercrimes, identity theft is one of the most common. Many Nigerians have been victims of identity theft, with hackers using phishing and social engineering techniques to obtain their financial information via harmful internet links and cloned applications [32]. Arguably, the fear resulting from prior negative experiences reduces trust in online applications [73]. This could explain why our Nigerian participants process their privacy decisions by the privacy calculus rather than relying on trust heuristic [34]. It is possible that individuals do not rely on trust when dealing with a financial application, and rely on the possible gains and losses resulting from their interaction with the financial application studied in this research. Overall, we recommend that more research be conducted to fully understand and investigate the relationship between trust and disclosure decisions. A Washington Post report indicated a general distrust in government across African countries, for example, Nigeria had a low trust for government at just 32% [23]. This could influence trust perceptions in general and encourage Nigerians to make their decisions by relying on variables other than trust.

6.2 Gender and Privacy Decision-Making

Men are more likely than women to access and use Information Communication Technology tools, particularly in developing countries [64]. Our study negates this expectation as women employed trust to influence gain-seeking evaluation of disclosure decisions as the perceived disclosure benefits were more important. In comparing the decision-making process of men and women, we found that men and women exhibited statistically significant differences in how they use perceived benefits to make disclosure decisions. This may not necessarily suggest that men and women would disclose more information than the other, but rather that men and women would disclose more information if they have a higher perception of benefits. Overall, men and women differ in the way they use perceived benefit to make disclosure decisions and how they use trust to perceive sensitivity. Nigerian women are also more likely

Table 6: Multi-group analysis results, showing path coefficients (B) and significance (p) for women, for men, and their difference (Men-Women). Among the 5 hypothesized gender differences, two are significant (difference p-values in bold). DIS = Disclosure, REC = Recommendation Quality, SEN = Sensitivity, TRU = Trust β= Path coefficient, p =p-value.

	β Women	p Women	β Men	p Men	β Men-Women	p Men vs Women
REC → DIS (H6a)	0.84	0.00	0.67	0.00	-0.18	**0.05**
SEN → DIS (H6b)	0.02	0.84	0.00	0.98	-0.01	0.88
TRU → DIS (H6c)	-0.06	0.28	-0.04	0.67	0.02	0.82
TRU → REC (H6d)	0.44	0.00	0.29	0.01	-0.16	0.19
TRU → SEN (H6e)	-0.42	0.00	-0.09	0.51	0.24	**0.01**

to reduce their perception of the sensitivity of personal information if they trust the other party. From the differences observed in the perception of benefits between men and women, the similar disclosure behaviour between men and women could imply that women are closing the digital skill gap. The similarity in privacy decision-making between men and women is also in line with the gender similarity index, which states that men and women from childhood to adulthood are more alike than different on most psychological variables [8, 31].

Results from our study comparing Nigerian men and women disclosure rates brings out an interesting perspective to the privacy research area. Contrary to previous studies that suggested that men tend to be more technically knowledgeable, hence, more privacy cautious and have a lower disclosure rate [18, 57, 78], our results indicate that Nigerian women have lower disclosure rates than men. In a Nigerian society, women live under the authority and care of others, such as their parents (if unmarried) and their spouses [6]. Their behavior is being scrutinized by others and may be questioned upon any unfavorable event. As a result, they may make careful assessments of the benefit of disclosing or withholding an information.

The significant difference in men and women's disclosure rate and privacy decision-making process gives new insights into privacy decision-making research in Nigeria. It sets precedence for additional research to examine further underlying factors affecting trust heuristics and privacy calculus. Our results indicate that people make privacy decisions using privacy calculus constructs (primarily perceived recommendation quality—i.e. benefits), but they also use trust heuristics to help them with these decisions, as they may have no other information to determine the extent of said benefits at the time of disclosure. This strengthens the view that privacy calculus and trust heuristics complement each other in terms of understanding users' privacy decisions [75].

6.3 Nigeria vs United States

Comparing our findings from Nigeria with those of Anaraky et al.[21] from the United States, We find that users from both Nigeria and the United States employ a hybrid process that combines heuristics, such as considering the perceived trust of the app—with calculated evaluations of the benefits and costs of disclosure. These similarities may be attributed to processes such as globalization which are increasingly undermining the social and physical differences between and amongst peoples [25]. For instance, there is an emerging global culture which tends to produce similarities in behavioral dispositions manifestation and patterns which may include social constructs such as perceived benefits, risks and trust in online applications [48]. The international media epitomized on the internet plays critical roles in this regard. Also, this global culture is shaped by the technology of applications available over the Internet and that this technology is mainly developed in WEIRD countries. In Nigeria for instance, the internet penetration in Nigeria rose from about 105 million in 2018 to over 143 million people in 2022 which implies that over 60 percent of the Nigerian population have access to the internet [51], hence Nigerians can access these applications developed on the ubiquitous internet thereby shaping their behavioural dispositions.

Comparing the specific findings of our study with Anaraky et al. [21], We find that in both studies participants' trust in the app did not directly influence their information disclosure decisions, but rather trust influenced respondents' perception of the sensitivity of the information and the quality of the recommendation. In contrast, whereas in Anaraky et al.'s [21] US sample disclosure behavior was significantly influenced by perceived sensitivity but not perceived recommendation quality, our Nigerian sample shows the opposite effect: the disclosure behavior of Nigerian study participants was significantly influenced by perceived recommendation quality but not perceived sensitivity. This finding may imply that our Nigerian participants—and especially the women participants—exhibited more gain-seeking behavior (focusing on the benefits of disclosure) when compared with their US counterparts. For example, a Nigerian national daily newspaper reports that unemployment and poverty, drives the constant desire to seek financial benefits online amongst Nigerians [69].

6.4 Limitations and Future Work

Even though the study's higher-level goal was to promote inclusiveness, our limited resources restricted us from recruiting a truly diverse sample in terms of age and country. Future studies could consider more African countries and a more diverse population. Our study considered how men and women made privacy decisions in the context of financial applications. Future research should look at diverse domains, such as health, entertainment, dating, and sociability, to see if our findings are applicable beyond the context of the financial domain.

The impact of culture and personality features on privacy decision-making is another relevant subject to investigate. Cultural and personality differences may influence the privacy decisions of people [26]. Future research could investigate the effects of culture and personality simultaneously on the decision-making process when it comes to privacy. We focused on an African country in this study; thus, we invite other researchers to explore the factors that affect privacy decision-making in other nations.

A major limitation is that disclosure decisions were evaluated in a study context and participants may have a different disclosure behaviour outside the study context when interacting with financial applications in the real world. This limitation is necessary to avoid an unethical study.

6.5 Implications for Practice

In privacy research, one objective is to assist users in making well-informed decisions. Due to the very few privacy research from Nigeria or Africa at large, Nigerian's may have been left out of the privacy consideration of digital products. Our findings indicate that it is critical to demonstrate the benefits of sharing information online to Nigerians. However, it may be necessary to incorporate trust and emphasize benefits when designing for Nigerian women. This finding suggests that researchers should concentrate their efforts on learning more about Nigerian men's perceptions of the benefits of disclosure.

Our study showed that users are eager to share information with third parties if they believe it will benefit them (recommendation quality). This is positive news for the future data-based economy, in which consumers will be able to contribute personal information in exchange for a better quality of life. Also, this creates the possibility of exchanging knowledge in exchange for various forms of rewards. For instance, improving living and health standards is a public good (i.e., 85.29% Nigerians were willing to collect the Covid-19 vaccines and were not bothered by factors such as their personal data being collected [56]). Users may derive immediate benefits from providing their data to improve public services such as national security, urban planning, traffic control, and mobile communication. Users may not directly trust a government or institution, but they may be prepared to share information if they believe it would help or benefit them. Hence, to motivate people from Nigeria to disclose more information, designers should focus on stressing the benefit they would get if the disclosure improves the recommendation quality.

In contrast to the US, our results suggest that Nigerian policy-makers should be careful in adopting US strategies to promote privacy-protective behaviors: unlike US consumers, Nigerians are more likely to increase their disclosure tendencies after learning about potential benefits of disclosing information. For example, the benefit of getting quick loans to solve immediate financial problems drive Nigerians to patronize loan sharks that blackmail them with sensitive information (phone contacts, images) provided during registration [14, 43].

7 CONCLUSION

In this paper, we investigated the underlying factors that influence privacy decision-making among Nigerians. Additionally, we investigated whether men and women differ on how they make information disclosure decisions in the context of a financial application. This paper contributes to privacy research by showing that Nigerians will make disclosure decisions based on their perception of the benefits and would instead use trust to form their opinion on benefits and risks. Furthermore, Nigerian women are more careful when making disclosure decisions by considering trust to influence their perceived sensitivity and benefits, which is then used to make disclosure decisions. In examining disclosure rates, Nigerian women were also found to have fewer disclosures rate when compared to men. This research closes an important research gap by investigating a non-WEIRD country. Most existing works have mainly focused on people from the WEIRD countries. Understanding the underlying mechanics of privacy decisions of Nigerians and Africans at large can assist product developers and designers to better support consumer's privacy decision-making processes during policy, design, and development of digital products.

ACKNOWLEDGMENTS

Rita Orji's research is supported by the Canada Research Chairs Program and the Natural Sciences and Engineering Research Council of Canada (NSERC) through the Discovery Grant. We also want to acknowledge the Federal University of Technlogy, Minna for their support.

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A APPENDICES

SECTION 1

1. What is your average monthly income ?
   - ....
   - I prefer not to say
2. What is your total amount of debt?
   - ....
   - I prefer not to say
3. What is the sum of your account balance?
   - ....
   - I prefer not to say
4. What is your estimated annual savings?
   - ....
   - I prefer not to say
5. What is your estimated annual expenses?
   - ....
   - I prefer not to say
6. What is your estimated financial worth?
   - ....
   - I prefer not to say
7. What is your living situation with regards to housing?
   - ....
   - I prefer not to say
8. How much do you spend on utility bills monthly ?
   - ....
   - I prefer not to say
9. How much do you spend on transportation monthly ?
   - ....
   - I prefer not to say
10. How many dependents do you have ?
   - ....
   - I prefer not to say

SECTION 2: Survey Questions Thank you for using the wedeliver app. Please answer all questions in this section. Demographic information 1 What is your age?

- 18- 24 years old
- 25 – 34 years old
- 35 – 44 years old
- 45 – 54 years old
- Over 55

2. What is your gender:
   - Man
   - Woman
   - Others (please specify) . . . .
4. What is the highest level of education you have completed?
   - High School or equivalent
   - College diploma
   - Bachelor's degree
   - Master's degree
   - Doctoral degree
   - Other . . . .

5. What is your country of residence ? . . . .

SECTION 3 Recall that the WEDELIVER app you saw is designed to help you with your financial situation. Please answer all questions in this section.

How sensitive did you perceive each of the questions asked on the Wedeliver app? 1. What is your average monthly income?

- Not at all sensitive
- Somewhat Sensitive
- Neutral
- Sensitive
- Very Sensitive

2. What is your total amount of debt?

- Not at all sensitive
- Somewhat Sensitive
- Neutral
- Sensitive
- Very Sensitive

3. What is the Sum of your bank account balances?

- Not at all sensitive
- Somewhat Sensitive
- Neutral
- Sensitive
- Very Sensitive

4. What is your estimated annual savings?

- Not at all sensitive
- Somewhat Sensitive
- Neutral
- Sensitive
- Very Sensitive

5. What is your estimated monthly expense?

- Not at all sensitive
- Somewhat Sensitive
- Neutral
- Sensitive
- Very Sensitive

6. What is your estimated financial worth ?

- Not at all sensitive
- Somewhat Sensitive
- Neutral
- Sensitive
- Very Sensitive

7. What is your living situation with regards to housing? (Rented, owned with mortgage, owned paid in full):

- Not at all sensitive
- Somewhat Sensitive
- Neutral
- Sensitive
- Very Sensitive

8. How much do you spend on utility bills (Internet, Calls, Electricity bills) monthly?

- Not at all sensitive
- Somewhat Sensitive
- Neutral
- Sensitive
- Very Sensitive

9. How much do you spend on transportation monthly?

- Not at all sensitive
- Somewhat Sensitive
- Neutral
- Sensitive
- Very Sensitive

10. How many dependents do you have?

- Not at all sensitive
- Somewhat Sensitive
- Neutral
- Sensitive
- Very Sensitive

SECTION 4 To what extent do you think that disclosing information below can improve recommendations for your personal financial health? How well do you agree with the following statements?

1. Disclosing information about my Monthly income can improve financial planning and recommendations made to me.

- Strongly Agree
- Agree
- Neither Agree or Disagree
- Disagree
- Strongly Disagree

2. Disclosing information about my total Amount of debt can improve financial planning and recommendations made to me.

- Strongly Agree
- Agree
- Neither Agree or Disagree
- Disagree
- Strongly Disagree

3. Disclosing information about the sum of my account balance can improve financial planning and recommendations made to me.

- Strongly Agree
- Agree
- Neither Agree or Disagree
- Disagree
- Strongly Disagree

4. Disclosing information about my estimated annual savings can improve financial planning and recommendations made to me.

- Strongly Agree
- Agree
- Neither Agree or Disagree
- Disagree
- Strongly Disagree

5. Disclosing information about my estimated monthly expenditure can improve financial planning and recommendations made to me.

- Strongly Agree
- Agree
- Neither Agree or Disagree
- Disagree
- Strongly Disagree

6. Disclosing information about my estimated financial worth can improve financial planning and recommendations made to me.

- Strongly Agree
- Agree
- Neither Agree or Disagree

- Disagree
- Strongly Disagree

7. Disclosing information about living housing condition can improve financial planning and recommendations made to me.

- Strongly Agree
- Agree
- Neither Agree or Disagree
- Disagree
- Strongly Disagree

8. Disclosing information about my monthly utility bills (Internet, Calls, Electricity bills) can improve financial planning and recommendations made to me.

- Strongly Agree
- Agree
- Neither Agree or Disagree
- Disagree
- Strongly Disagree

9. Disclosing information about my monthly transportation expenses can improve financial planning and recommendations made to me.

- Strongly Agree
- Agree
- Neither Agree or Disagree
- Disagree
- Strongly Disagree

10. Disclosing information about the number of my dependents can improve financial planning and recommendations made to me.

- Strongly Agree
- Agree
- Neither Agree or Disagree
- Disagree
- Strongly Disagree

SECTION 5 Please answer all questions in this section How well do you agree with the following statements? 1. I believe that Wedeliver is trustworthy in handling my information

- Strongly Agree
- Agree
- Neither Agree or Disagree
- Disagree
- Strongly Disagree

2. I believe WEDELIVER tells the truth and fulfills promises related to the information I provide

- Strongly Agree
- Agree
- Neither Agree or Disagree
- Disagree
- Strongly Disagree

3. I believe WEDELIVER tells the truth and fulfills promises related to the information I provide

- Strongly Agree
- Agree
- Neither Agree or Disagree
- Disagree
- Strongly Disagree

4. I believe WEDELIVER is honest when it comes to using the information I provide

- Strongly Agree
- Agree
- Neither Agree or Disagree
- Disagree
- Strongly Disagree

5. I believe WEDELIVER is predictable and consistent regarding the usage of my information

- Strongly Agree
- Agree
- Neither Agree or Disagree
- Disagree
- Strongly Disagree