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How Students' Information Sensitivity, Privacy Trade-Offs, and Stages of Customer Journey Affect Consent to Utilize Personal Data

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Abstract

Aim/Purpose	This study aimed to increase our understanding of how the stages of the customer purchase journey, privacy trade-offs, and information sensitivity of different business service sectors affect consumers' privacy concerns.
Background	The study investigated young consumers' willingness to provide consent to use their personal data at different phases of the customer journey. This study also examined their readiness to provide consent if they receive personal benefits, and how information sensitivity varied between different individuals and business sectors.
Methodology	Data was collected by a quantitative survey (n=309) and analyzed with R using the Bayesian linear mixed effect modeling approach. The sample consisted of university students in Finland, who represented a group of young and digitally native consumers. The questionnaire was designed for this study and included constructs with primarily Likert-scale items.
Contribution	The study contributed to data privacy and consent management research in information sensitivity, privacy trade-off, and the customer journey. The study underlined the need for a stronger user experience focus and contextuality.
Findings	The results showed that readiness to disclose personal data varied at different phases of the customer journey as privacy concerns did not decrease in a linear

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fashion throughout the purchase process. Perceived benefits affected the willingness to provide consent for data usage, but concerned consumers would be less trade-off oriented. Self-benefit was the most relevant reason for sharing, while customization was the least. There is a connection between the information sensitivity of different business sector information and privacy concerns. No support for gender differences was found, but age affected benefits and business sector variables.

Recommendations for Practitioners
The study recommends approaching consumers' data privacy concerns from a customer journey perspective while trying to motivate consumers to share their personal data with relevant perceived benefits. The self-benefit was the most relevant benefit for willingness to provide consent, while customization was the least.

Recommendations for Researchers
The study shows that individual preference for privacy was a major factor directly and via interaction for all three models. This study also showed that consumers' subjective decision-making in privacy issues is both a situational and a contextual factor.

Impact on Society
This study could encourage policymakers and societies to develop guidelines on how to develop privacy practices and consent management to be more user centric as individuals are increasingly concerned about their online privacy.

Future Research
This study encourages examining consumers' motivational factors to provide digital consent for companies with experimental research settings. This study also calls to explore perceived benefits in all age groups from the perspective of different information in various business sectors. This study shows that privacy concern is a contextual and situational factor.

Keywords
data privacy, information sensitivity, privacy concern, trade-offs, customer journey

INTRODUCTION

Consumers leave data about their behavior behind when interacting with various information technology solutions. Companies use consumers' data to develop their operations, personalize their services, and optimize and strengthen their relationships with customers (Alamäki et al., 2018; Rust & Huang, 2014). However, consumers have become more concerned about how their online behavior is analyzed and how their data is used. Furthermore, according to several data privacy regulations, most companies need digital consent from customers to utilize their data. Thus, privacy practices and consent management have become a challenge for companies in developing online services and marketing activities (Al-Adwan, 2019; Hemker et al., 2021; Liyanaarachchi, 2021). Optimized privacy practices can even improve companies' market share and increase their revenue (Eggers et al., 2022).

We approached privacy concerns and consumers' perceived trade-off benefits from an individual perspective. The sample consists of university students in Finland, who represent young consumers with typically limited financial resources to spend on online services and electronic commerce. However, they have learned to use various online channels in purchasing services and small items, such as Netflix, Spotify, pizza orders, and public transportation tickets. In this study, data privacy referred to individuals' claim to determine when, how, and to what extent information about them is communicated to others (Malhotra et al., 2004). Consumers typically weigh the benefits of data disclosure against any 'sacrifice' it represents (Lanier & Saini, 2008) and may seem to focus on the trade-off between 'sacrifice' (private information) and 'price' in some kind of consumer value-creation process. Hence, at the heart of most privacy practices is the trade-off between the costs and benefits of disclosing one's personal information (e.g., Eggers et al., 2022; Lanier & Saini, 2008) and consumers' risk-benefit evaluation and risk assessment that may sometimes be even irrational (e.g., Barth & de Jong, 2017). Thus, the privacy paradox has also gained attention among academics (Barth et al., 2019) but the relationship and meaning of data-privacy concerns to preferences within the customer journey have been much less discussed (Martin & Murphy, 2017). The customer journey has been researched from visualization, service process, and customer experience perspective (Følstad & Kvale, 2018), but the connection of the customer journey to data privacy has been less discussed (Aiello et al., 2020). Although the literature on data privacy provides a rather broad review of privacy concerns, research on the preferences of privacy trade-offs, customer journey, and business sector perspective is scarce. Similarly, more research is needed regarding the role of the customer purchase journey and privacy trade-offs from consumers' preferences (Schweidel et al., 2022). This study contributes to filling the aforementioned research gaps by emphasizing the role of the customer purchase journey and privacy trade-offs from the perspective of consumers' preferences. The research question for this study is the following:

> *RQ:* How do the stages of the customer purchase journey, privacy trade-offs, and information sensitivity of different business service sectors affect consumers' privacy concerns?

This paper is presented in four sections. After this introduction, customer privacy concerns and the customer journey is discussed in the context of a framework for the study. Then, the key themes and variables are defined to develop hypotheses. After the methodology section, we discuss the results and managerial implications of our findings.

THEORETICAL FRAMEWORK AND HYPOTHESIS DEVELOPMENT

DECISION-MAKING UNDER UNCERTAINTY

Providing consent for companies to use personal information in business is both an emotional and cognitive decision-making situation for consumers in the digital world. The digital environment and its various data strategies have created several privacy-sensitive contexts and situations for consumers while they are making decisions on the Internet (Bornschein et al., 2020; Quach et al., 2022; Wu et al., 2020). Several theories of human decision-making reveal that individuals optimize decisions between situational (Terborg, 1981; Wu et al., 2020) and conditional (Einhorn & Hogarth, 1981) factors. The consumers' subjective decision to accept the consent for collecting and using their personal information involves situational-related risks that cause the emotion of uncertainty among consumers. The emotion of uncertainty is an essential part of individuals' subjective decision-making process where they weigh benefits and losses (Heilman et al., 2010; Kahneman & Tversky, 1979). Thus, consumers evaluate potential benefits and losses while making decisions to accept digital consent when using online services (Bornschein et al., 2020). Thus, the privacy paradox (Barth et al., 2019) and privacy tension in the digital world (Quach et al., 2022) have gained attention among academics. The decision-making of individuals is more often based on choices or other short-run initiatives than careful evaluation processes for finding an optimal alternative (Einhorn & Hogarth, 1981). The trigger theory (Roos et al., 2004) shows that various external triggers can influence consumers' behavioral changes by creating a reason to begin to consider switching or selecting a digital consent. In fact, prior research on privacy calculus theories (Culnan & Armstrong, 1999; Fernandes & Pereira, 2021) has pointed out that fairness-related practices and privacy trade-offs positively affect consumers' willingness to provide consent. Therefore, they function as external triggers in a consent-related decision-making situation. Since decision-making is also situational, we predict that customer purchase journeys and information from various business sectors also affect the decision-making process while considering the acceptance of digital consent.

Privacy Concerns Cause Uncertainty Among Consumers

The development of marketing practices using consumer data and analytics has advanced rapidly in recent years, which has raised even more data privacy concerns among consumers (Eggers et al., 2022). The degree of privacy concern differs between individuals (Chellappa & Sin, 2005). Older users were less likely to disclose their information due to usability problems (Kisekka et al., 2013) but all studies have not found differences due to age (e.g. Markos et al., 2017). Age seems to be a contextual factor for privacy concerns. Healthy adults have higher security and privacy concerns than the ailing elderly population (Wilkowska & Ziefle, 2012), which shows correlations between privacy concerns and personal situations. Some consumers are more willing than others to allow companies to use their personal information for commercial purposes. For example, women have higher security and privacy concerns than men (Wilkowska & Ziefle, 2012), meaning that demographics may be associated with privacy concerns. Consumers were also more permissive of data collection if they felt a firm's data collection processes were fair (Culnan & Armstrong, 1999). However, sharing personal data over public Internet networks may cause privacy concerns regarding the protection of personal information (Chen & Zhao, 2012). Additionally, gender differences in information sensitivity have been shown, as women were less likely to provide their cell phone numbers than men in one study (Acquisti & Gross, 2006).

H1: Gender will affect data privacy concerns such that females require more privacy

H2: Age will affect data privacy concerns but it is affected by situations

There is growing concern among consumers about having to reveal personal information, and many are dissatisfied with companies' data practices. This concern may be a major problem hampering growth in digital consumer services where advanced data analytics and artificial intelligence (AI) systems are changing and reshaping value chains and ecosystems (Kariuki et al., 2021; Valkokari et al., 2018). Privacy concerns are a typical negative outcome customers may feel while using digital services. This vulnerability creates potential risks for companies and makes consumers concerned (Almajali, 2022; Martin et al., 2017). Thus, privacy concern greatly affects consumers' purchase behavior, and it is associated with the success of digital channels. Previous research (Bleier & Eisenbeiss, 2015; Chellappa & Sin, 2005; Wilkowska & Ziefle, 2012) has shown that individual factors and the features of service providers may raise privacy concerns among consumers. Consumers may become concerned about potentially negative financial, functional, physical, temporal, and social outcomes (Laroche et al., 2003). Perceived risk is a significant determinant of privacy concerns (Dinev et al., 2013). Additionally, individuals do not make the same estimate when they evaluate potentially negative outcomes or risks (Sjöberg, 2000; Tan, 1999). For example, some consumers feel that Internet shopping is riskier than shopping in conventional stores (Tan, 1999). However, in adopting mobile applications, users seem to rank privacy as a low priority (Barth et al., 2019; Kelley et al., 2013). In addition, the effective aspects of user interfaces may also decrease privacy concerns (Kehr et al., 2015).

H3: Sense of good data privacy will be important for consumers

Customer Purchase Journey Behavior in a Data Privacy Context

Customer journey refers to the different touchpoints where customers interact with a brand, product, or service of interest and they form various customer experiences depending on the phases of the customer journey where they interact (Wolny & Charoensuksai, 2014). Thus, the customer purchase journey can be described as the repeated interactions between a service provider and consumer during sales negotiations, information sharing, and value exchange (Johnson et al., 2021). Customer journeys are also defined as a series of touchpoints that customers go through before, during, and after purchase (Becker et al., 2020). Følstad and Kvale (2018) underline that customers' behavior is typically analyzed according to predefined and structured steps such as awareness, familiarity, consideration, purchase, and loyalty. The framework of analysis of the current study was conducted according to this division of customer journey phases.

Companies collect information from different digital touchpoints in the customer journey when consumers are searching, purchasing, and using products and services digitally and physically (Hallikainen et al., 2018). Companies have built omni-channel delivery and communication strategies and means to fulfill consumer expectations. One option is to share consumer data back for use by original consumers. An example of this reverse use of consumer data and a framework relating to it have been discussed by Saarijärvi et al. (2014). Search engines play a critical role when companies try to reach customers during the early stages of a customer purchase journey. Behavioral targeting of online shops connects consumers with product and service brands based on data relating to their past online behaviors. The data that they leave behind could comprise web pages they have visited, time spent on each page, and the products they collected in their online shopping baskets (Yu et al., 2017). All these aforementioned data management actions, which are based on collected consumer data, take place in conversions during a customer purchase journey. Mäki and Alamäki (2019) showed that consumers are the most willing to share their data after actual sales contact when they have already purchased a product or service. Aiello et al. (2020) found that asking for personal data at the end of the customer journey increased consumers' disclosure of personal data.

H4: Privacy concern decreases at the end of the customer journey

Trade-Off of Personal Information

Service providers and retailers can influence consumers' willingness to allow them to collect and use personal data in their business engineering and operations in various ways. Global giants, such as Facebook, Google, LinkedIn, and other social media service providers freely share their applications with consumers if they accept their privacy policy. Receiving free digital applications and services is one of the most typical ways consumers benefit from a trade-off, and service providers may use their information commercially. Prior research (Chellappa & Sin, 2005; Krafft et al., 2017; Lin et al., 2022; Steinfeld, 2015) has shown that if consumers gain personal value from allowing service providers to collect their personal information, then they are more willing to permit data collection.

In digital content marketing, companies provide useful digital material, such as white papers or webinars, to potential consumers if they share their content information with service providers (Järvinen & Taiminen, 2016). In these cases, companies offer a trade-off to consumers that ensures they can collect and save consumer-related information for marketing and sales purposes (Caudill & Murphy, 2000). In addition to educational or entertaining digital material, the positive incentives of trade-off may focus on the personalization of digital services (Chellappa & Sin, 2005) or entertainment and consumer information control (Krafft et al., 2017). The users also evaluate trade-offs in relation to a situation that indicates that privacy is a situational factor (Kehr et al., 2015). Hence, companies collect consumers' personal usage information and use it to personalize services, but they can also share some of the information back for their consumers to use. Saarijärvi et al. (2014) presented real-life cases of the "reverse use of customer data," in which companies created win-win situations with consumers regarding data collection. In these cases, companies used consumer data to create recommendations or visibility for consumers, while they used it for business development and marketing purposes.

H5: Trade-off will increase consumers' willingness to share their personal data

H6: Concerned consumers will be less trade-off oriented

Information Sensitivity and Different Business Sectors

Consumers may view all types of information differently, but information type also affects consumers' privacy concerns (Dinev et al., 2013; Malhotra et al., 2004; Phelps et al., 2000). Dinev et al. (2013) showed that consumers evaluated the sensitivity of the information. Similarly, business and service sectors differ from each other (Mäki & Alamäki, 2019). Prior research (Edvardsson et al., 2008; Mitra et al., 1999) has shown that the type of service business and type of product or service purchased also affect the degree of consumers' perceived uncertainty and risk. Consumers' perceived or actual behavior may also be different in different business or service sectors as it is a context-dependent phenomenon (Alamäki et al., 2022). Additionally, buying processes and interactions require more cognitive processing when purchasing unknown or complex services than when interacting with simple daily services (Kaski et al., 2018). The information companies collect through digital channels include personal characteristics, product preferences, purchase history, financial transactions, and emotional preferences related to brands, products, or services. However, consumers differ from each other regarding their information sensitivity and the types of information they find most sensitive (Acquisti & Gross, 2006; Phelps et al., 2000; Wilkowska & Ziefle, 2012). In addition, consumers feel less concerned about privacy issues if they were dealing with more trusted retailers (Bleier & Eisenbeiss, 2015; Chellappa & Sin, 2005) and if they can control the sharing of their personal information (Phelps et al., 2000). Financial and personal identification information is usually considered more sensitive than other information (Phelps et al., 2000). Similarly, consumers are sensitive in sharing their personal health information (Lafky & Horan, 2011). In general, Acquisti and Gross (2006) showed that consumers are less willing to provide accurate information than more general information. According to Acquisti and Gross (2006), accurate information includes sexual orientation and political views. General information is easier to observe or acquire in another way, because it is more visible than context-dependent information that is often business sector related, such as health information. In this study, business sector information refers to the information that every business sector collects, manages, and processes in the customer processes.

H7: Business sector information will affect consumers' data privacy concern

Methodology

Research Data

Data were collected from university students of a university of applied sciences in Finland, who represented young consumers of service companies. There were 309 responses, of which 293 were complete, and 16 contained partial data. Most respondents were women (67%, n = 200 of 301 respondents who provided demographic data) with a mean age of 29.7 years (29.1 years for men and 30.0 years for women) with a standard deviation of 9.95. The sample included students from an applied university, who typically are studying their first undergraduate degrees or are career changers or continuous learners from various age groups. Participants were sent an email that included a web link to the questionnaire. All participants who answered the questionnaire were invited to participate in a lottery that gave them the chance to win minor gifts.

Respondents were asked to rate value using a 5-point Likert scale ranging from 5 (*totally agree*) to 1 (*totally disagree*). Questions were grouped into five groups from A to E as listed in Tables 1 and 2. For the purposes of analysis, the scales in groups B–E were converted such that larger magnitudes of response corresponded to a preference towards higher levels of privacy. Consumers with preferences towards higher levels of privacy were less likely to share private data or allow its usage. We called the response for groups of interest (C–D) *privacy level*. Higher privacy level values meant that consumers were less likely to share data and vice versa.

Table 1. **Questionnaire items and their wording and reference**

Construct	Wording	Reference
Privacy sensitivity	I am sensitive to the way companies handle my personal information. It is important to keep my privacy intact from online companies. Personal privacy is very important, compared to other subjects. I am concerned about threats to my personal privacy.	Adopted from Martin et al. (2017)
Trade-off (value)	I authorize a company to use my customer data if I receive value from it. I authorize to use my data if I receive free service as compensation. I authorize to use my data if I receive customized experiences. I authorize to use my data if it saves my time in doing business.	Adopted from Martin et al. (2017)
Information sensitivity	I do not feel comfortable with the information that … a) insurance companies b) municipal healthcare centers c) leisure hobby places d) private healthcare centers e) grocery stores … collect from me.	Adopted from Dinev et al. (2013)
Customer journey	Would you allow (yes/no) a company to utilize your data when you ... a) search for information about products and services b) compare products or services c) buy a product d) contact the company after the purchase e) share your experiences related to products	Self-developed. This classification is derived from the typical definition of the customer journey as a series of touchpoints that consumers go through before, during, and after purchase (e.g. Becker et al., 2020).

Table 2. Summary of questionnaire components, number of items, data, and response types

Group (label)	Items	Data type	Type	Family (link)
A (gender and age)	2	Mixed (binary, continuous)	predictor	
B (privacy sensitivity)	7	Ordinal (5-point Likert)	predictor	
C (information trade-off)	4	Ordinal (5-point Likert)	response	Cumulative (logit)
D (business sensitivity)	5	Ordinal (5-point Likert)	response	Cumulative (logit)
E (customer journey)	5	Boolean (no/yes)	response	Bernoulli (logit)

DATA ANALYSIS

Data were analyzed using R version 3.6.0 (https://www.r-project.org). First, we used Cronbach's alpha (Cronbach, 1951) to determine the internal consistency of questionnaire items in each scale, starting with question group B. Then, we pooled responses by summing the scores of each scale, resulting in the variable *sensitivity*, which was considered continuous in the models. We used Spearman's rank correlation test to assess for a possible correlation between respondents' age and sensitivity. Then, we used the Wilcoxon rank sum test to test if the median sensitivity is different between men and female. Sensitivity was then used as a predictor in linear mixed-effect models (Gelman & Hill, 2007). In order to account for differences in scales and compatibility with priors in Bayesian regression, both numeric predictors (age and sensitivity) were considered continuous and were standardized (zero mean with unit variance) before model estimation. Gender was converted into a binary variable by setting *male* as 1 without other transformations.

For the mixed-effects models, we adopted a Bayesian framework (Kruschke & Liddell, 2018) using the R package Brms version 2.9.0 (https://github.com/paulbuerkner/brms; Bürkner, 2017) with RStan version 2.18.2 (https://mc-stan.org; Carpenter et al., 2017). We assumed that our observed Likert response variables originated from the categorization of latent (unobservable), normally distributed continuous variables (Bürkner & Vuorre, 2019). We estimated three models, one for each group; C (model 1), D (model 2), and E (model 3) with four-item, five-item, and five-item categories, respectively (see Table 1). There were between 293 and 298 respondents in each group. Models were independent for each group, and their complexity was chosen by comparing the leave-one-out (LOO) cross-validation scores (Vehtari et al., 2017) of nine model candidates with varying levels of complexity.

For models 1 and 2, which had 5-point ordinal responses, we used a cumulative normal distribution with equal variance assumption, and for model 3, which had a Boolean response, we used a Bernoulli distribution (Bürkner & Vuorre, 2019). The link function was fixed to Logit for all models. Models were run with five chains and 6000 iterations per chain (the first 3000 were for a warm-up) using the NUTS sampling method (Hoffman & Gelman, 2014). We set the 'adapt_delta' sampling parameter to 0.95 (default 0.8) to improve convergence, and all other parameters were kept at their defaults (including prior distributions and parameters). After fitting the models, we used posterior distributions to extract point estimates and differences between parameters using the posterior probability for differences, including zero, when given the data. For this, we used the Brms function 'hypothesis.' For illustration purposes, we also computed marginal effects for selected variables by setting covariates at their mean values and plotting the estimates with their distributions using the Brms function 'marginal_effects.' For easier visual inspection of model predictions, we considered responses continuous, that is, between [1,5] for TRADEOFF and BUSINESS and [0,1] for JOURNEY.

All variables of regression models are depicted in Figure 1 with the seven hypotheses (H1-H7) associated with their corresponding variables. In the regression models, scenarios predictors associated with groups C, D, and E enter the models as independent categorial intercepts, which are applied in predicting the responses. Age, gender, and sensitivity are included in each model as background predictors.

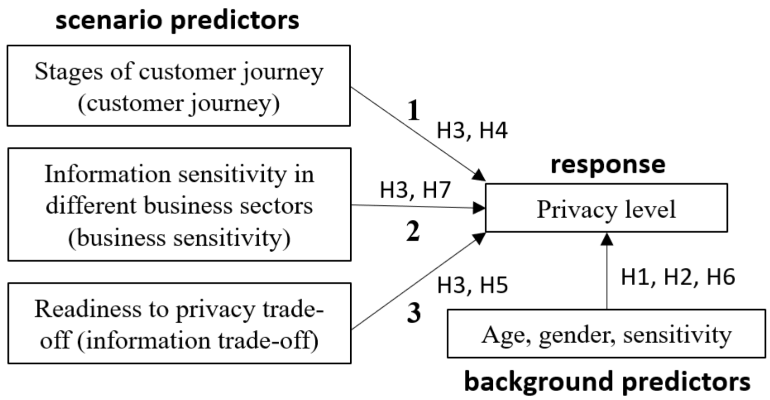

Figure 1. Research models and hypotheses H1-H7
(We fitted three different regression models (1, 2, and 3) for privacy level preference, each adjusted by background predictors of age, gender, and sensitivity.)

RESULTS

Cronbach's alpha for items in group B (n = 301) was 0.89, indicating good internal consistency (Kline, 2000). We computed the total sensitivity score for each respondent by summing all seven questions. The mean of the resulting scores was 27.8 (SD 5.6). A total of 32 respondents had the maximum possible sensitivity score of 35, and two respondents had a minimum score, which was 7 (Figure 2). There were no statistically significant correlations between privacy concerns and age (correlation 0.092; $p = 0.111$) or gender (z-score 1.201; $p = 0.230$).

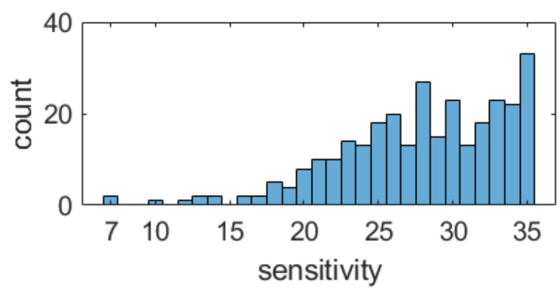

Figure 2. Histogram of total sensitivity score variable, which was formed from seven sub-questions (N = 301)
(A higher score dictated more sensitivity with less willingness to share private data.)

After testing nine linear models, we chose the following model for the final analysis: Privacy level ~1 + X + (gender + age + sensitivity):(1 + X) + (1|Subject), where X was the group-specific factor for the variable TRADEOFF (four levels; n = 293), BUSINESS (five levels; n = 298), or JOURNEY (five levels; n = 297). Hence, for variable group C-D (Table 2), responses appear on the left-hand side of the formula, while group-specific factors are on the right-hand side. In addition to intercepts, the model contained three individual predictors and three interactions (symbol ":") and was a good compromise between model complexity and fit. In particular, the BUSINESS group was biased towards more complex models, while the JOURNEY group fit best with simple ones. For random effects, intercepts were sufficient. The effective sample size for all models and studied parameters was at least 4000. After fitting the above model (with response-specific family functions and logit link) for the data in the three groups (C, D, and E), we computed illustrative marginal plots for the main effects. These are depicted in Figure 3 with the highest density intervals of 95% and 99%.

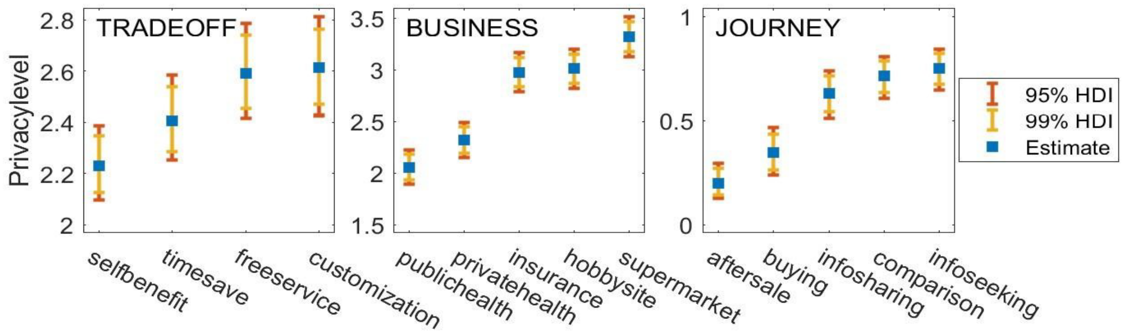

Figure 3. Predicted responses for item groups C, D, and E

Each point estimate (arranged in increasing order) represents the conditional response at the means of the covariates (age, gender, and sensitivity) with the highest density intervals of the posterior distributions at 95% and 99%. Ordinal responses were taken as continuous for easier visual comparison.

Next, we checked for evidence that estimated parameters (three) or their differences (6 × 4 = 24 for group C and 10 × 4 = 40 for groups D and E) differed from zero. For this, we computed the posterior probability (PP) as 2 × min (*r*, 1-*r*), where *r* was the ratio of posterior samples above zero. We were interested in PP values below 0.05, which we considered significant. Results for TRADEOFF, BUSINESS, and JOURNEY are shown in Tables 3, 4, and 5, respectively. For all three tables, we have omitted data for interactions between item category and gender (24, 40, and 40), as PP was > 0.05 for these parameters. For gender, we used effect coding that set a positive correlation between the increase in "Privacy level" for men, indicated by the variable label "Gender[male]" (and vice versa for women). In particular, the covariate age had a strong effect on the response (five PP values below 0.05). This is illustrated in Figure 4, which depicts the predicted marginal effects in population responses as a function of age for all five item categories.

Table 3. Model coefficients for TRADEOFF (group C)

Variable/contrast	Value	PP	Value	PP	Value	PP
			Age:		**Sensitivity:**	
selfbenefit – freeservice	**-0.99**	**<.001 *****	-0.20	2.4E-1	-0.17	.34
selfbenefit – customization	**-1.04**	**<.001 *****	-0.01	9.7E-1	-0.21	.23
selfbenefit – timesave	**-0.52**	**.003 ****	0.14	4.1E-1	**-0.46**	**.009 ****
freeservice – customization	-0.05	.77	0.20	2.5E-1	-0.04	.82
freeservice – timesave	**0.46**	**.006 ****	**0.34**	**4.6E-2 ***	-0.29	.10
customization – timesave	**0.51**	**.004 ****	0.15	3.9E-1	-0.25	.15
Age	0.12	.48				
Gender[male]	0.56	.11				
Sensitivity	**0.58**	**<.001 *****				

Model coefficients for TRADEOFF (group C) for population main effects (first three columns) and two-way interactions (last four columns). We have reported the estimated difference of coefficients with the two-tailed posterior probability (PP) of the model to include zero with the thresholds <0.001 (***), <0.01 (**), and <0.05 (*). n = 293.

Table 4. Model coefficients for BUSINESS (group D).

Variable/contrast	Value	PP		Value	PP		Value	PP	
				Age:			Sensitivity:		
insurance – publichealth	**2.07**	**<.001**	***	-0.06	6.9E-1		0.10	.56	
insurance – hobbysite	-0.07	.66		**-0.51**	**1.7E-3**	**	**-0.33**	**.041**	*
insurance – privatehealth	**1.44**	**<.001**	***	-0.16	3.1E-1		-0.03	.85	
insurance – supermarket	**-0.72**	**<.001**	***	0.22	1.7E-1		**-0.76**	**<.001**	***
publichealth – hobbysite	**-2.14**	**<.001**	***	**-0.44**	**6.5E-3**	**	**-0.43**	**.012**	*
publichealth – privatehealth	**-0.63**	**<.001**	***	-0.09	5.7E-1		-0.13	.44	
publichealth – supermarket	**-2.79**	**<.001**	***	0.28	9.2E-2		**-0.86**	**<.001**	***
hobbysite – privatehealth	**1.51**	**<.001**	***	**0.35**	**3.0E-2**	*	0.30	.076	
hobbysite – supermarket	**-0.65**	**<.001**	***	**0.73**	**1.3E-4**	***	**-0.43**	**.012**	*
privatehealth – supermarket	**-2.16**	**<.001**	***	**0.38**	**2.2E-2**	*	**-0.73**	**<.001**	***
Age	-0.06	.68							
Gender[male]	0.49	.11							
Sensitivity	**0.66**	**<.001**	***						

Model coefficients for BUSINESS (group D) for population main effects (first three columns) and two-way interactions (last four columns). We have reported the estimated difference of coefficients with the two-tailed posterior probability (PP) of the model to include zero with the thresholds <0.001 (***), <0.01 (**), and <0.05 (*). n = 298.

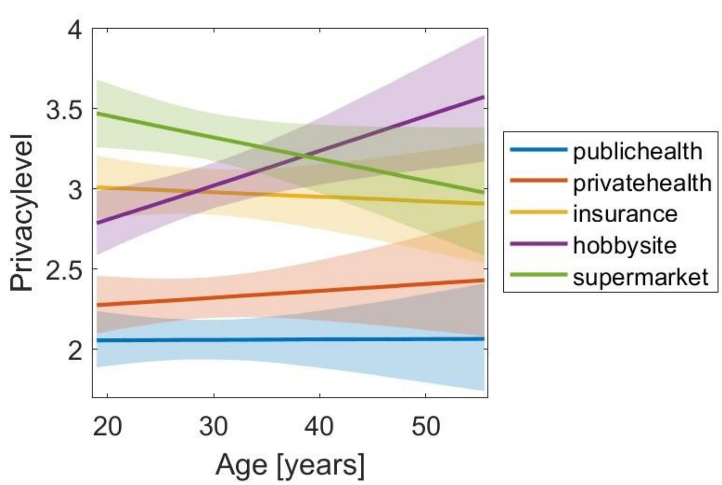

Figure 4. Predicted population responses as a function of the covariate age for the BUSINESS group

The lines in Figure 4 represent the marginal effects of each factor at the means of the covariates (gender and sensitivity) with the highest density intervals of the posterior distribution at 95%. The ordinal response was taken as continuous for easier visual comparison. Older people were more hesitant to share their data with a hobby site than younger people, but the situation was reversed for a supermarket. Age did not affect the sensitivity of the information that public and private healthcare and insurance companies collect.

Table 5 shows population main effects (first three columns) and two-way interactions (last four columns). We have reported the estimated difference of coefficients with the two-tailed posterior probability (PP) of the model to include zero with the thresholds <0.001 (***), <0.01 (**), and <0.05 (*), n = 297. The hypotheses and results are listed in Table 6.

Table 5. Model coefficients for JOURNEY (group E)

Variable/contrast	Value	PP		Value	PP	Value	PP	
				Age		Sensitivity		
infoseeking – comparison	0.19	.43		0.64	1.8E-1	0.08	.74	
infoseeking – buying	**1.75**	**<.001**	***	0.18	6.9E-1	-0.03	.91	
infoseeking – aftersale	**2.51**	**<.001**	***	-0.29	5.5E-1	**0.50**	**.049**	*
infoseeking – infosharing	**0.57**	**.016**	*	-0.15	7.4E-1	0.15	.52	
comparison – buying	**1.57**	**<.001**	***	-0.45	3.2E-1	-0.11	.67	
comparison – aftersale	**2.32**	**<.001**	***	-0.92	5.7E-2	0.42	.089	
comparison – infosharing	0.38	.096		-0.79	9.4E-2	0.07	.74	
buying – aftersale	**0.76**	**.002**	**	-0.47	3.1E-1	**0.53**	**.041**	*
buying – infosharing	**-1.18**	**<.001**	***	-0.34	4.6E-1	0.18	.47	
aftersale – infosharing	**-1.94**	**<.001**	***	0.14	7.6E-1	-0.35	.16	
Age	0.18	.33						
Gender[male]	0.10	.81						
Sensitivity	**1.13**	**<.001**	***					

Table 6. Hypotheses and results

Hypotheses	Result	Description
H1: Gender will affect data privacy concerns such that females require more privacy	Not supported	For all three models, men had higher privacy demands (that is, higher Privacylevel scores) than women. However, this difference was insignificant for all main and interaction effects. No support for gender differences in privacy concerns was found.
H2: Age will affect data privacy concerns but it is affected by situations	Supported	Age was an important factor for TRADEOFF and BUSINESS. However, the linear coefficient was significantly non-zero (PP <0.05) only via interactions, not by itself. We found a significant interaction effect between age and the tradeoff between the costs of privacy disclosure and the

Hypotheses	Result	Description
		benefits of free services and saving time. With a notably higher coefficient for the free service than saving time, we can conclude that older people favored time-saving benefits in exchange for their private data. Also, older people were more hesitant to share their data with a hobbysite than younger people, but the situation was reversed for a supermarket.
H3: Sense of good data privacy will be important for consumers	Supported	When comparing privacy levels between different contexts, significant differences (PP <0.05) were found for 22 of the 26 comparisons, thus indicating that context mattered a lot in the need for privacy. Individual preference for privacy (sensitivity predictor), was a major factor itself for all three models, and also via interactions (9 of the 26). Sensitivity itself did not depend on gender or age.
H4: Privacy concern decreases at the end of customer journey	Partly supported	This hypothesis was supported for all journey stage pairs except infoseeking vs. comparison and comparison vs. infosharing, which were at the earliest and latest stages of the journey and where consumers were strictest regarding their privacy. Sensitivity significantly affected infoseeking vs. aftersale and buying vs. aftersale by augmenting the differences. Consumers were more willing to disclose data close to the actual buying phase, not just at the beginning or end of the customer journey when they are sharing experiences. The named customer journey phases were: (a)search for information about products and services, (b) compare products or services, (c) buy a product, (d) contact the company after the purchase, and (e) share your experiences related to products.
H5: Trade-off will increase consumers' willingness to share their personal information.	Supported	There were significant differences between all pairs except freeservice vs. customization. Self-benefit was the most relevant reason for sharing, while customization was the least.
H6: Concerned consumers will be less trade-off oriented.	Supported	Sensitivity had a significant main effect on consumers' willingness to trade-off. Sensitivity had a significant interaction effect only in the most extreme scenarios (that is, selfbenefit vs. timesave), where the higher score increased the gap between these two.
H7: Business sector information will affect privacy concerns.	Supported	Differences between business sectors were significantly high (PP <0.001) between all pairs of sectors except insurance vs. hobbysite, where no significant difference was present. Most of the differences (six out of 10) were further augmented by sensitivity being higher.

DISCUSSION

THEORETICAL CONTRIBUTION

This study has made several theoretical contributions. We found that individual preference for privacy was a major factor directly and via interaction for all three models. This study also showed that consumers' subjective decision-making in privacy issues is both a situational and contextual factor. The privacy concern varied between the stages of the customer purchase journey and the type of business sector information affected by the information sensitivity. The study supports also the trigger theory (Roos et al., 2004) by showing that different benefits do not make a similar effect on the willingness to provide digital consent. Similarly, this study is aligned with findings that consumers' interest affects privacy concerns positively (Li et al., 2023).

In this study, our gender-related hypothesis was not supported. Gender was not related to privacy concerns, and although men had higher privacy demands than women, this difference was not statistically significant. Our findings did not align with prior research (Acquisti & Gross, 2006; Wilkowska & Ziefle, 2012), which found that women had significantly higher privacy concerns than men. Age was not significantly related to privacy concerns in this study, but it did affect privacy concerns in terms of the benefits trade-off and when the business sector was taken into account. This supported prior research that consumers' uncertainty regarding privacy is context-dependent (Fernandes & Pereira, 2021; Markos et al., 2017). Consumers who have little privacy concern, in general, might have greater levels of privacy concern when dealing with certain business sectors. Our findings showed that older respondents valued their privacy more when sharing hobby-related data than data regarding their supermarket shopping habits. In addition, older people favored saving time over getting free services in exchange for their data.

The results also showed that phases of the customer journey affected consumers' privacy concerns, thus partly supporting our hypothesis. In other words, consumers had different levels of privacy concerns at different phases of the purchase process. Searching for new information and comparing alternatives differed statistically from the buying and aftersales phases. The earliest and final stages of the customer journey differed from the other stages. Respondents were strictest regarding their privacy during the earliest and final stages of the purchase process. Sharing of personal customer experiences was included in the customer journey study. Thus, unlike the study by Aiello et al. (2020) indicated, privacy concerns did not decrease linearly throughout the purchase process. Rather, it formed two curved peaks. This pattern may have occurred because consumers need to provide personal information when buying products or services for the first time or after sales, but searching for information, comparing alternatives, and sharing personal experiences do not normally require data sharing. This supported prior research (e.g., Fernandes & Pereira, 2021) that consumers' privacy behavior is situational and depends on their position in an online journey.

This study supported the hypothesis that the benefits consumers receive when they allow the use of their personal data influences their privacy-related consumer behavior. Different benefits resulted in a different level of willingness to consent to data use among consumers. Personal benefits were most likely to affect trade-off behavior. Receiving customized services had less impact than personal benefits, time-saving, and free services. Retailers, service providers, and other sellers may increase consumers' motivation to consent to data collection by offering certain benefits. This shows that privacy concern is a dynamic psychological state that can be manipulated by triggers. Hence, the trigger theory (Roos et al., 2004) supports also the privacy trade-off behavior of consumers. In addition, respondents had varying trade-off orientations. Concerned consumers were less trade-off oriented than those who were less concerned. Thus, a similar motivational trigger may create different responses among consumers. Thus, this study supports the findings of prior studies (e.g., Quach et al., 2022) that show there is tension between companies' goals and consumers' privacy expectations, as consumers expect relevant benefits from the use of their personal data.

This study confirmed the finding that information type and business context affects privacy concerns (Dinev et al., 2013; Fernandes & Pereira, 2021; Malhotra et al., 2004). Different business sectors deal with different types of information, causing varying levels of information sensitivity. Differences between business sectors were significant, except when information was related to insurance or hobbies. Respondents considered healthcare information the least sensitive, whereas data collected in the supermarket was the most sensitive. We concluded that consumers needed to allow the use of their personal healthcare data to receive high-quality care at the doctor's office or hospital, whereas visiting a supermarket generally does not require consumers to allow data collection. Age affected respondents' information sensitivity regarding information about their hobbies and supermarket shopping habits.

Managerial Implications

The digital landscape is larger than ever, and the number of tools available for companies to analyze and use data in marketing and business operations has increased in recent years. In addition, the speed at which new analytic tools enter the markets is accelerating. The study has practical implications, especially for electronic commerce companies and digital marketing, and sales practitioners who are planning to develop their digital marketing practices and consent management from the consumers' viewpoint. This study recommends approaching consumers' data privacy concerns from a customer journey perspective while trying to motivate consumers to share their personal data with relevant perceived benefits. The results of this study strengthen our understanding that privacy practices and consent management are important for companies in developing digital marketing and sales (Al-Adwan, 2019; Hemker et al., 2021; Liyanaarachchi, 2021). The study by Eggers et al. (2022) states that optimized privacy practices can improve companies' market share and increase their revenue.

The results of this study show that consumers seem more favorable towards data-based interaction with companies in the latter phases of the customer journey. In practical terms, this means that data should be used to offer individualized services or products when the consumer is in 'buying mode.' This takes place in the latter parts of the customer journey when a consumer has bought a product or at least indicated a strong interest in the offering. This contrasts with typical 're-marketing' or 'retargeting,' in which browsing history data analytics aggressively guide marketing activities for potential consumers at the very early stages of the customer journey. Perceived benefits affected consumers' willingness to provide consent for data usage, but concerned consumers would be less trade-off oriented. This finding recommends practitioners profile consumers and create more information to build trust among consumers who are less trade-off oriented. For digital marketing and sales practitioners, it is an important finding that self-benefit was the most relevant reason for willingness to provide consent, while customization was the least. Companies also need to consider the type of their business sector information as it affects consumers' privacy concerns, as there is a connection between information sensitivity of different business sector information and privacy concerns.

Limitations and Future Research

Our study was based on a sample of relatively young adults who represent university students in the Finnish consumer culture. Our results apply to this consumer segment and cannot be generalized to all populations or other countries. Privacy concerns may differ between countries (Markos et al., 2017). However, our sample represented digital natives, a consumer segment whose importance is increasing. Our results clarified privacy concerns during the different phases of the customer journey of this digitally-advanced consumer group. In addition, we analyzed the consumer impressions about data privacy concerns during the customer journey adopted by Solomon et al. (2016). In reality, customer journeys differ from this conceptual model, and they may exist in several forms, especially on digital platforms. More research is needed to investigate the privacy concerns of consumers within this multidimensional and versatile customer journey reality. Furthermore, more examination is needed to understand how different benefits affect different consumers' willingness to share private information in a way that creates deeper consumer understanding. The results of this study should encourage researchers to explore the effects of different digital media, such as social media, videos, and augmented and virtual reality on privacy concerns as we need more understanding of the contextual and motivational factors.

CONCLUSIONS

The current study has contributed to consumer data usage practices among young university students. The results have several conclusions. First, companies should have a clear consumer focus in all data-related operations. Our study indicated that data privacy is an important issue for consumers in general. Second, data analytics and utilization should be approached using a customer journey framework. Third, businesses should plan and analyze consumers' trade-off patterns. A positive tradeoff between the costs and benefits of data disclosure increases consumers' willingness to share their personal information. Finally, consumers seem to have different ideas about disclosing their personal data in different business or service industries. Consumers are less willing to share their personal data for company use with businesses in industries that limit the amount of consumer information they process or when they offer services of low overall significance. Overall, our study underlined the need for a strong consumer focus in all data-driven activities. The customer experience may be violated if consumers are targeted early or very late in the customer journey. This study encourages researchers to explore deeper privacy concerns and perceived benefits while consumers in all age groups are accepting digital consent as part of their customer's digital purchase journeys.

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