2025.07.09

How do Consumers Manage Their Privacy in a Generative AI Environment? Consumer Classification and its Implications

Juhyeon Kim[1], Siwon Kim[1], Minyoung Huh[2], Jeeyeon Sah[3]

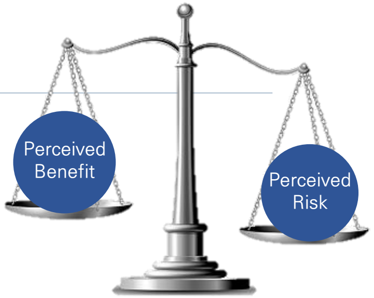
[1]Master Degree Student, Dept. of Consumer Science, Seoul National University

[2]Lecturer, Dept. of Consumer Science, Chungbuk National University

[3]Assistant Professor, Dept. of Consumer Science, Seoul National University

Table of Contents

1. Background



- Generative AI offers various benefits but requires sharing personal data in exchange
- Individual's privacy is perceived to be context- dependent, varying on specific situations (Laufer & Wolfe, 1977)
- According to the Privacy Calculus Model, consumers weigh potential benefits and losses before disclosing personal data (Laufer & Wolfe, 1977)
- However, in situations even when privacy risks are recognized, many do not engage in protective actions (Gerber et al., 2018), and the gap between attitudes and behaviors is known as the "privacy paradox"
- This mismatch stems from immediate rewards, lack of control, trust issues, or information asymmetry (Acquisti & Gross, 2006; Gerber et al., 2018)

This study's goal is to…

- Examine the gap between consumer awareness and response behavior
- Classify consumers by perceived benefit, perceived risk, and privacy management
- Identify characteristics and differences across user types

2. Research Questions and Methodology

(1) Research Question

RQ1

1. How are generative AI users classified based on their perceived benefits, perceived risks, and privacy management behaviors?

- ✓ Method: K-means clustering

RQ2

2-1. What are the demographic characteristics and digital response tendencies of each user group?

- ✓ Method: ANOVA

2-2. How do future service usage intentions and expectations · outlook for AI technologies differ across user types?

- ✓ Method: ANOVA

2. Research Questions and Methodology

(2) Measurement Design

Category	Variable	Details	Items	Scale type
Demographic	Gender	Male=1, Female=2	1	categorical
	Age	20s=1, 30s=2, 40s=3, 50s and above=4	1	categorical
	Education level	High school and below=1, College enrolled and above=2	1	categorical
	Perceived SES	Below average=1, Average and above=2	1	categorical
	Monthly household income	Under 400M KRW=1, 400~500M KRW=2, 500~600M KRW=3, 600~700M KRW=4, Over 700M KRW=5	1	categorical
	Occupation	Office workers=1, Non-office workers=2, Students/housewives/unemployed=3	1	categorical
Benefit		Items measuring the various benefits that users may experience when using generative AI	5	continuous
Risk		Items measuring the various concerns or perceived risks associated with the use of generative AI	3	continuous
Privacy management		Items measuring users' privacy management behaviors aimed at protecting personal information when using generative AI	4	continuous
Digital competence		Items measuring users' ability to identify trustworthy information and detect fraudulent content in a digital information environment	4	continuous
Information sharing intention		Items measuring consumers' willingness to provide personal information when using a service	6	continuous
Choice demand		Items measuring the extent to which consumers expect to retain control over their choices when using AI-based recommendation services	3	continuous
Risk prospect of AI technologies		Items measuring consumers' anxieties and expectations regarding the potential impact of AI and related technologies	4	continuous
Service Area		Medical, Finance, Education, Media, Leisure, Work	6	continuous

Table 1. Measurement Design

2. Research Questions and Methodology

(3) Sample Characteristics

- Utilized data source from 2023 Intelligent Information Society User Panel Survey(by KCC & KISDI)
- Final sample: 509 adults who only responded to generative AI-related items

Category		Frequency (%)	Category		Frequency (%)
Gender	Male	248(49)	Age	20s	146(28.7)
	Female	261(51)		30s	169(33.2)
Monthly household income	Under 400M KRW	146(28.7)		40s	96(18.9)
	400~500M KRW	90(17.7)		50s and above	98(19.3)
	500~600M KRW	105(20.6)	Education level	High school and below	102(20.0)
	600~700M KRW	101(19.8)		College enrolled and above	407(80.0)
	Over 700M KRW	67(13.2)	Occupation	Office workers	260(51.1)
Perceived SES	Below average	14(2.8)		Non-office workers	170(33.4)
	Average and above	495(97.2)		Students/housewives /unemployed	79(15.5)

Table 2. Demographic characteristics of respondents

2. Research Questions and Methodology

(4) Validation of Measurement Tools

- Conducted CFA to assess convergent validity for 3 main factors (Benefit, Risk, Privacy management)

Variable	Measurements	Factor Loading	AVE	CR	α	M (SD)
Benefit	It helps reduce boredom.	0.72	0.36	0.73	0.73	3.63 (.53)
	It is good for killing time.	0.69				
	It is useful for supporting learning activities (e.g., language learning, programming).	0.54				
	It helps me develop ideas.	0.52				
	It helps with time management.	0.47				
Risk	I am worried that I could be personally identified.	0.73	0.50	0.75	0.74	3.64 (.65)
	I am concerned that my privacy might be invaded.	0.73				
	I am afraid my personal information might be stored and used for AI learning.	0.65				
Privacy management	I avoid sharing passwords or security-related information.	0.86	0.69	0.90	0.90	3.36 (.94)
	I avoid sharing personal photos or videos.	0.86				
	I avoid sharing identifiable information of others (e.g., names, addresses).	0.80				
	I avoid sharing sensitive data (e.g., medical history, sexual orientation).	0.80				

Table 3. Confirmatory factor analysis results (Benefit, Risk, Privacy Management)

2. Research Questions and Methodology

(4) Validation of Measurement Tools

- Theoretical and empirical support for the Benefit variable's low AVE

Variable	Measurements	Factor Loading	AVE	CR	α
Benefit	It helps with time management	0.47	0.36	0.73	0.73

✓ **Factor Loading**

- Theoretical and content validity
  - Time-saving effects of generative AI observed in task duration studies (Noy·Zhang, 2023)
  - In healthcare, AI reduced physicians' documentation time, allowing more focus on patient care (Letko, D, 2023)
- Reliability of prior studies and item sources
  - Generative AI contributed to time management by accelerating information search during literature review process (Chauke, T. A et al, 2024)

✓ **AVE**

- Convergent validity is considered acceptable if CR ≥ 0.6, even when AVE 〈 0.5 (Fornell & Larcker, 1981)

2. Research Questions and Methodology

(4) Validation of Measurement Tools

- Discriminant validity

	Variable	Benefit	Risk	Privacy management	AVE
1	Benefit	1			.36
2	Risk	.67	1		.50
3	Privacy management	.40	**.07**	1	.69

Table 4. HTMT among factors and discriminant validity

	Variable	Benefit	Risk	Privacy management	AVE
1	Benefit	1			.36
2	Risk	.66(.44)	1		.50
3	Privacy management	.38(.14)	**.02**(.00)	1	.69

Table 5. Correlations among factors and discriminant validity

- Calculated HTMT values for more robust discriminant validity (Henseler et al., 2015)
- All HTMT values were below 0.85, indicating sufficient discriminant validity
- HTMT between Risk and Privacy Management was 0.07, showing clear distinction
- Correlation between these two factors was also low (HTMT = 0.07, r = 0.02)

2. Research Questions and Methodology

(4) Validation of Measurement Tools

- Scatterplots revealed a polarized distribution, suggesting no clear linear relationship
- Indicates that users with similar Risk perceptions show divergent privacy management behaviors

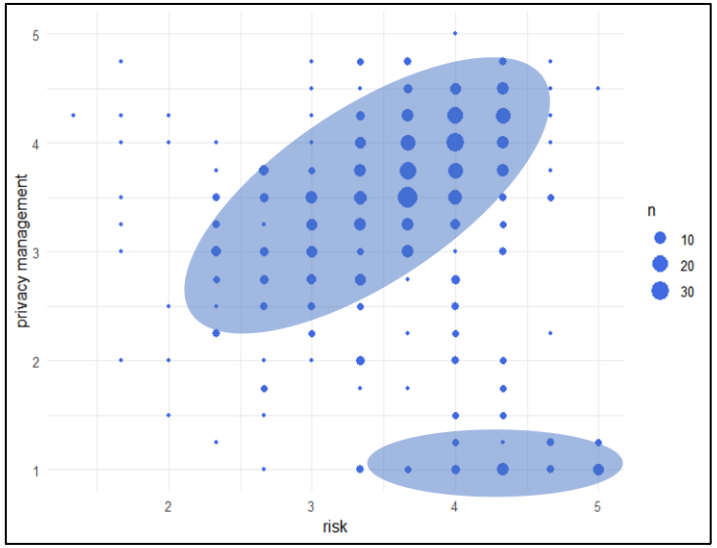


Figure 1. Scatterplot of perceived risk and privacy management

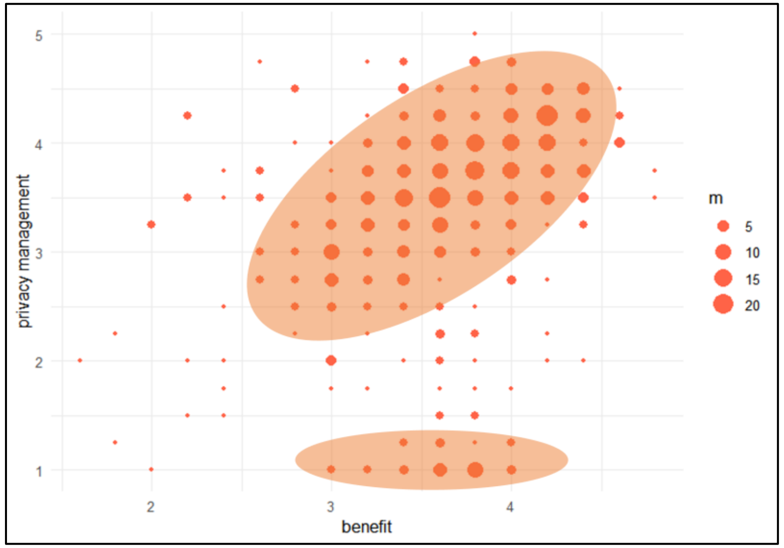


Figure 2. Scatterplot of perceived benefit and privacy management

⇒ used cluster analysis for user typology

3. Research Findings ① Cluster Analysis

(1) User Typology by Benefit, Risk, and Privacy management

Variable Final centroid value (SD)	Habitual managers (N=95)	Active managers (N=299)	Paradoxical users (N=51)	Unaware users (N=64)	F /Welch's F
Benefit	3.23(.51)[a]	3.87(.36)[c]	3.67(.26)[b]	3.03(.53)[a]	84.03***
Risk	2.84(.54)[a]	3.90(.34)[b]	4.33(.44)[c]	3.06(.55)[a]	170.72***
Privacy management	3.42(.38)[c]	3.89(.38)[d]	1.29(.41)[a]	2.42(49)[b]	688.38***

significantly higher

significantly lower

Table 6. ANOVA results: Cluster-wise differences in Benefit, Risk, and Privacy Management

- All factors showed significant group differences
- Reorganized perception and behavior into two dimensions for clearer cluster interpretation
  - Combined perceived benefit and risk as **'Situational Awareness'**
  - Classified privacy management as **'Response Behavior'** as it is defined as a practical behavior factor

3. Research Findings ① Cluster Analysis

(1) User Typology by Benefit, Risk, and Privacy management

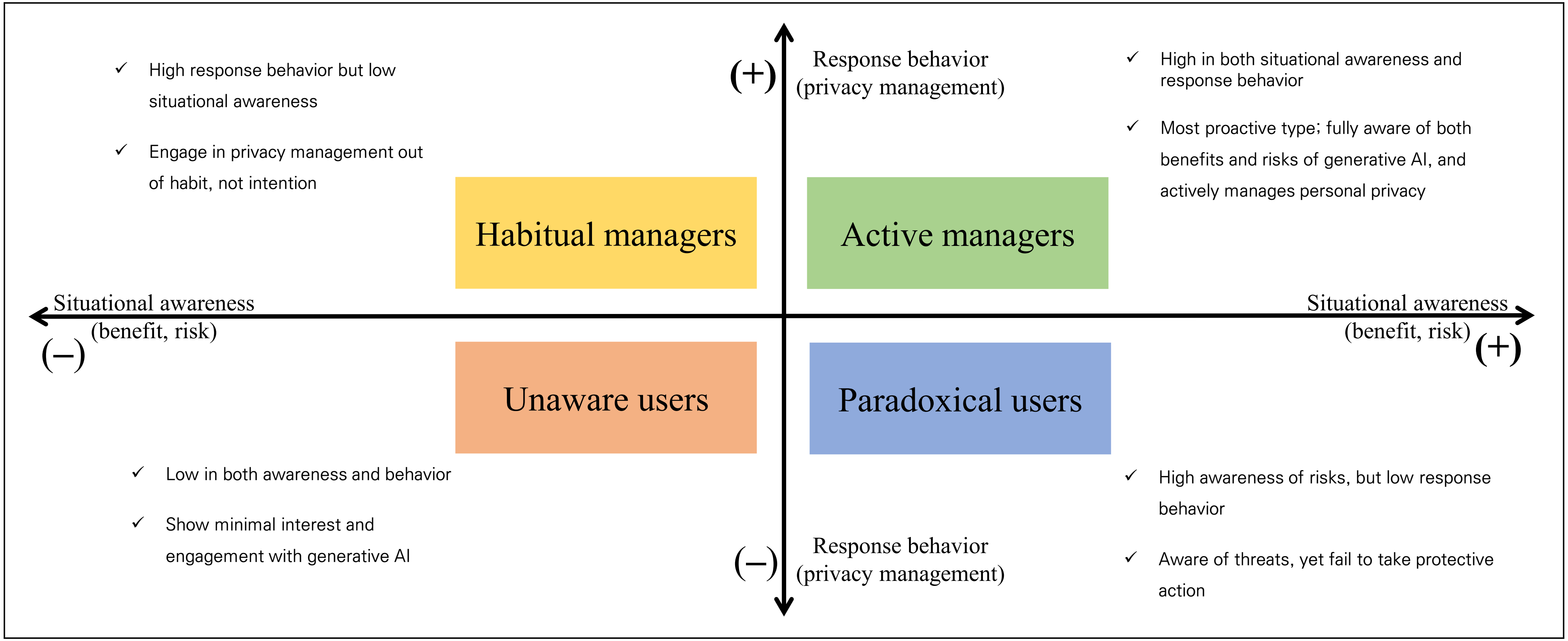


Figure 3. Four user types Based on situational awareness and response behavior

3. Research Findings ① Cluster Analysis

(2) Demographic Characteristics and Digital Response Tendencies by User Type

- Key consumer characteristics: Demographic characteristics, digital response tendencies
- Demographic characteristics(see p.5)
- Digital response tendencies

Variable	Measurements	Factor Loading	AVE	CR	α
Digital competence	Able to distinguish between advertising and informational content.	.81	.59	.85	.85
	Able to identify reliable information by comparing it with other sources.	.81			
	Able to verify the source of retrieved information.	.73			
	Able to distinguish fraudulent or deceptive websites.	.72			
Information sharing intention	Income	.77	.51	.86	.86
	Occupation/Workplace	.77			
	Health Information	.76			
	Educational Background	.71			
	Current Location	.66			
	Home Address	.57			

Table 7. Overview of measurement tools for Digital Response Tendencies (Digital competence, Information sharing intention)

3. Research Findings ① Cluster Analysis

significantly higher

significantly lower

(2) Demographic Characteristics and Digital Response Tendencies by User Type

Variable			Habitual managers (N=95)	Active managers (N=299)	Paradoxical users (N=51)	Unaware users (N=64)	x^2/Welch's F
Demographic	Gender	Male	49(19.8)	148(59.7)	27(10.9)	24(9.7)	3.97
		Female	46(17.6)	151(57.9)	24(9.2)	40(15.3)	
	Age	20s	30(20.5)	83(56.8)	14(9.6)	19(13.0)	12.03
		30s	22(13.0)	107(63.3)	17(10.1)	23(13.6)	
		40s	19(19.8)	51(53.1)	15(15.6)	11(11.5)	
		50s and above	24(24.5)	58(59.2)	5(5.1)	11(11.2)	
	Education level	High school and below	20(14.6)	89(65.0)	12(8.8)	16(11.7)	3.31
		College enrolled and above	75(20.2)	210(56.5)	39(10.5)	48(12.9)	
	Occupation	Office workers	54(20.8)	151(58.1)	27(10.4)	28(10.8)	7.85
		Non-office workers	31(18.2)	104(61.2)	12(7.1)	23(13.5)	
		Students/housewives/unemployed	10(12.7)	44(55.7)	12(15.2)	13(16.5)	
	Perceived SES	Below average	2(14.3)	8(57.1)	2(14.3)	2(14.3)	.45
		Average and above	93(18.8)	291(58.8)	49(9.9)	62(12.5)	
	Monthly household income	Under 400M KRW	28(19.2)	94(64.4)	10(6.8)	14(9.6)	51.23***
		400~500M KRW	18(20.0)	62(68.9)	4(4.4)	6(6.7)	
		500~600M KRW	27(25.7)	60(57.1)	7(6.7)	11(10.5)	
		600~700M KRW	19(18.8)	52(51.5)	12(11.9)	18(17.8)	
		Over 700M KRW	3(4.5)	31(46.3)	18(26.9)	15(22.4)	
Digital Response Tendencies	Digital Competence		3.31(.60)[a]	3.48(.92)[a]	**3.73(.46)[b]**	3.32(.55)[a]	8.98***
	Information sharing intention		2.92(.65)[bc]	**3.02(.82)[c]**	2.63(.47)[a]	2.65(.80)[ab]	9.24***

Table 8. ANOVA results: Cluster-wise differences in demographic characteristic and Digital Response Tendencies

3. Research Findings ② Difference Test

(1) Future Service Usage Intentions and Expectations · Outlook for AI Technologies by User Type

- Service-related factors (see p.5)
- AI-related expectation and outlook variables

Variable	Measurements	Factor Loading	AVE	CR	α
Risk prospect of AI technology	Will rely on AI systems that analyze data and make recommendations for most decisions.	.621	.341	.673	.668
	Individuals will lose control over how their data is used or handled.	.613			
	AI will identify people's psychological states or emotions to provide personalized services.	.588			
	Surveillance will become normalized, leading to more privacy intrusions.	.507			
Choice demand	Recommender systems should ensure users retain the right to reasonably use AI-based content.	.692	.342	.672	.669
	Recommender systems should allow users to control or limit exposure to unwanted content (e.g., news, ads).	.594			
	Recommender systems should continuously improve to ensure diversity of content for users.	.556			

Table 9. Overview of measurement tools for Expectations and Outlook for AI Technologies

- As in prior constructs, Convergent Validity was confirmed: Although AVE values were below 0.5, CR exceeded 0.6 (Fornell & Larcker, 1981)

3. Research Findings ② Difference Test

(1) Future Service Usage Intentions and Expectations · Outlook for AI Technologies by User Type

Variable		Habitual managers (N=95)	Active managers (N=299)	Paradoxical users (N=51)	Unaware users (N=64)	F /Welch's F
Service Area	Medical (Medical chatbot – disease diagnosis, symptom explanation)	3.51(1.22)[ab]	3.67(1.22)[b]	4.67(2.36)[c]	3.20(.69)[a]	9.90***
	Finance (Robo-advisor consultation, AI-based investment summary)	3.34(.66)[a]	3.60(.89)[b]	3.92(.84)[b]	3.27(.76)[a]	9.23***
	Education (Learning content creation, tutoring chatbot, performance analysis)	3.27(1.43)[a]	3.70(1.62)[ab]	3.92(.84)[b]	3.41(1.63)[ab]	4.50**
	Media (AI-based subtitle, translation, image/video generation)	3.40(1.13)[a]	4.04(1.93)[b]	3.94(.81)[b]	3.67(1.76)[ab]	6.06***
	Leisure (Travel recommendation chatbot, conversational characters in metaverse games)	3.28(1.15)[a]	3.69(1.54)[ab]	3.78(1.42)[b]	3.28(1.08)[a]	3.34*
	Work (AI-based document writing, meeting summary, data visualization)	3.37(1.24)[a]	3.78(1.55)[b]	4.08(1.06)[b]	3.19(.66)[a]	13.26***
	total	3.36(.73)[a]	3.75(.99)[b]	4.05(.66)[c]	3.34(.72)[a]	16.16***
Outlook for AI Tech	Choice demand	3.23(.55)[a]	3.76(.44)[b]	3.27(.71)[a]	3.06(.56)[a]	50.74***
	Risk prospect of AI technologies	3.22(.59)[a]	3.60(.46)[b]	3.36(.38)[a]	3.34(.57)[a]	16.11***

significantly higher

significantly lower

Table 10. ANOVA results: Cluster-wise differences across service areas and Expectations and Outlook for AI Technologies

4. Conclusion

- Research Implications

1. Strategic differentiation in service and policy design by user type

   - Significant differences were observed across all service domains, indicating that consumer acceptance of AI services varies by user type
   - In high-sensitivity domains (e.g., medical, finance, work), Paradoxical users and Active managers demonstrated strong service usage intentions

2. Diverse interpretations of the ‘Paradoxical user type'

Overconfident type

- ✓ High digital competence → may lead to overconfidence
- ✓ A need for feedback-based training or self-assessment tools to bridge the gap between perceived ability and actual behavior

Compliant type

- ✓ High level of usage and intention→ Tolerating risk to utilize AI technologies
- ✓ Represent a new user type driven by social or technological pressure

3. Limitations of the privacy concern vs. acceptance dichotomy

- Consumer acceptance of AI is shaped by complex interactions among situational awareness, digital competence, and response behavior
- Policy and service design should adopt typology-based approaches reflecting awareness-behavior dynamics

4. Conclusion

- Limitations

1. Theoretical Scope and Model Limitations
   - Privacy Calculus Model may not fully capture the complexity of real-world consumer behavior
   - Psychological factors (i.e. digital self-efficacy, trust, anxiety, fatigue) in digital context can influence behavior but were not included in this model
   - (Future direction) Apply extended theoretical framework that incorporates emotional & cognitive variables for a more nuanced understanding of consumer behavior

2. Content Validity and Item coverage
   - Items measuring perceived benefits were limited in scope, not fully reflecting varied contexts of actual AI usage
   - Items reflect early-stage use, focusing on convenience and information access than productivity and emotional support aspects
   - (Future direction) Develop additional items to reflect usage goals and contexts for better benefit measurement

EOD

How do Consumers Manage Their Privacy in a Generative AI Environment?
Consumer Classification and its Implications

Keywords: AI Technology / Privacy Paradox / Consumer Typology

Siwon Kim
siwonk37@snu.ac.kr