Research on the relationship between characteristics of AI recommendation services and usage intentions

- with a focus on the "perfect day"-

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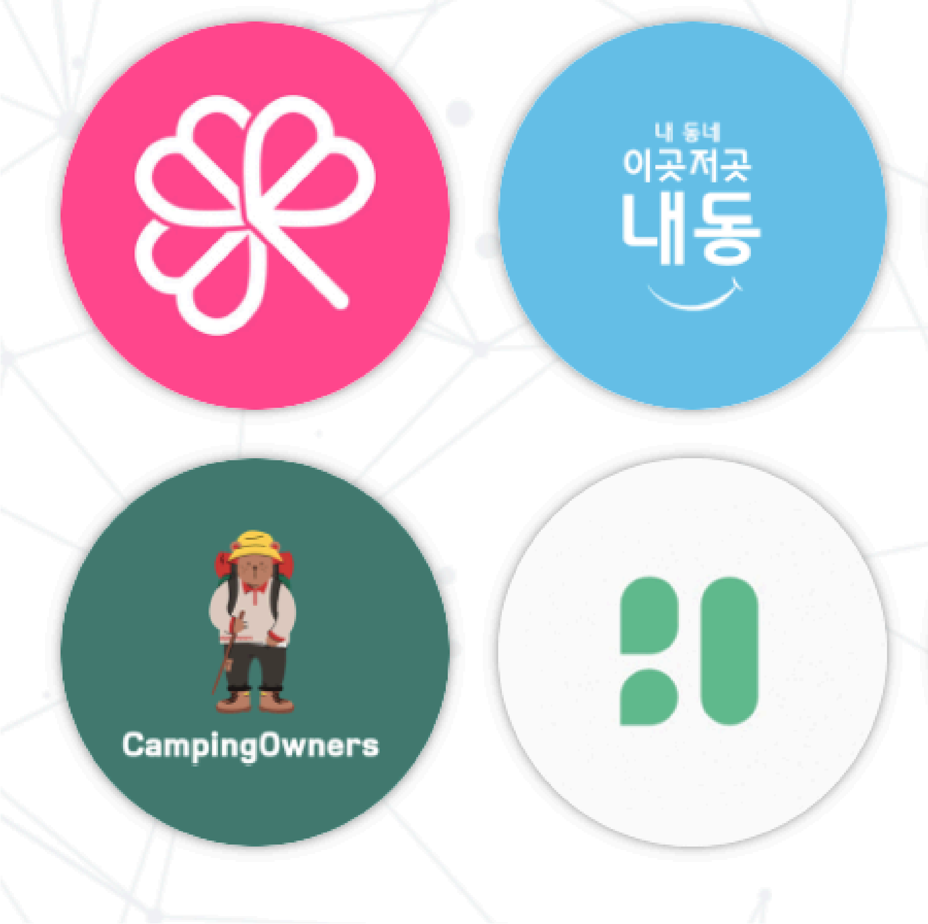
“NEWRUN“ enterprise association

뉴런즈

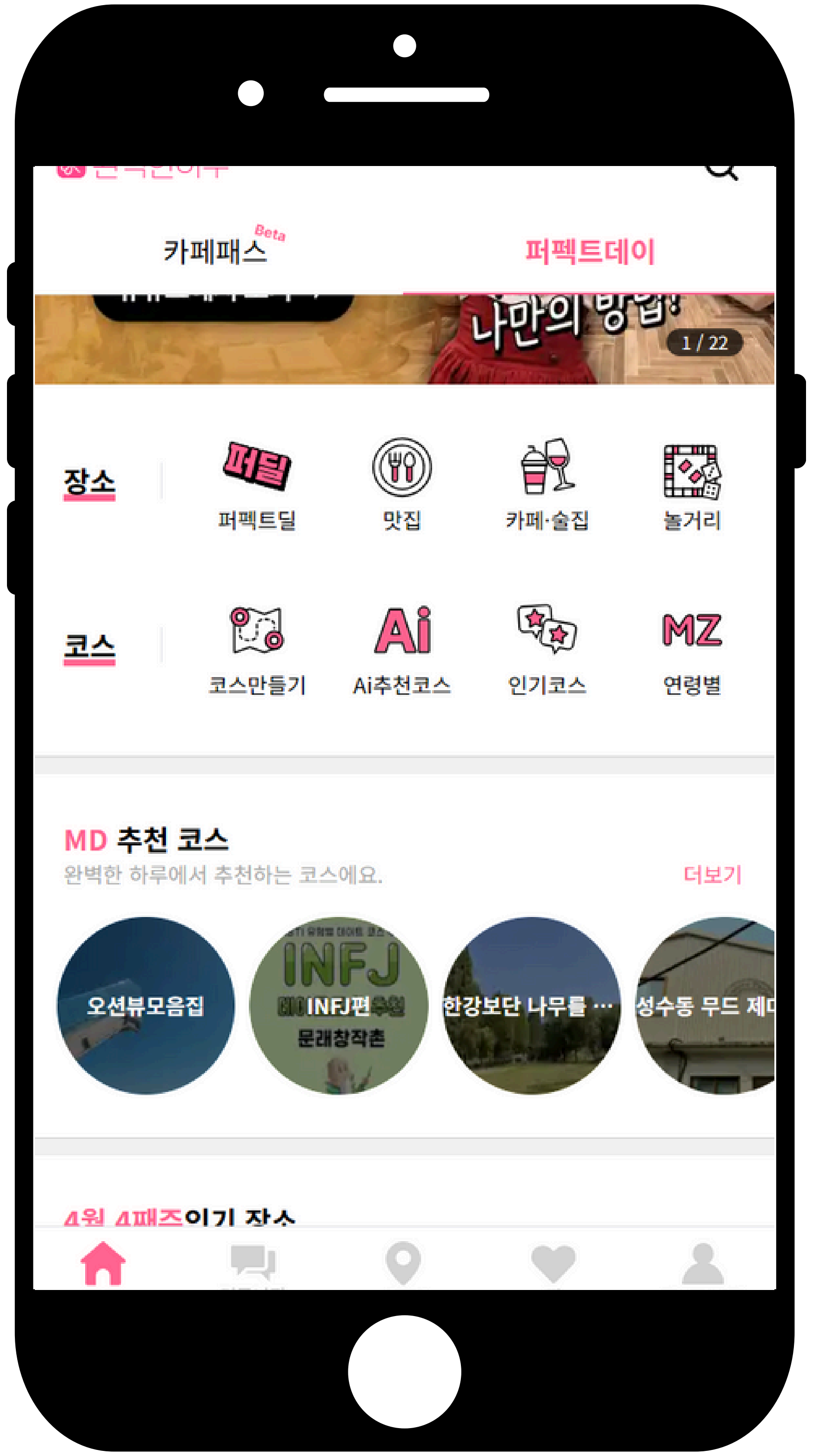
A company that specializes in building AI-powered applications, programs and data supply for AI-based applications and programs, and data to help customers with their businesses.



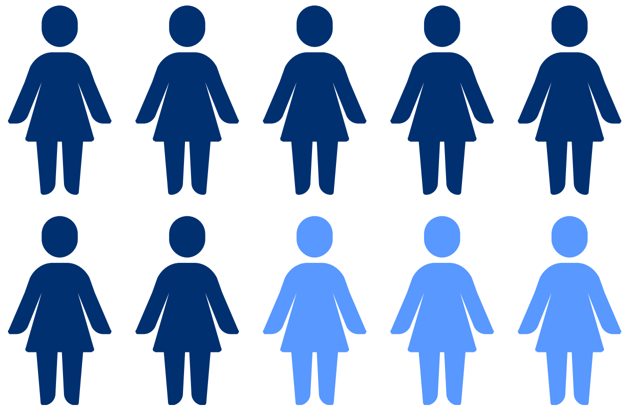
“A Perfect Day” application

What is a "Perfect Day"?

An application that helps you design a "build your own course" quickly and easily by recommending personalized venues based on your preferences.

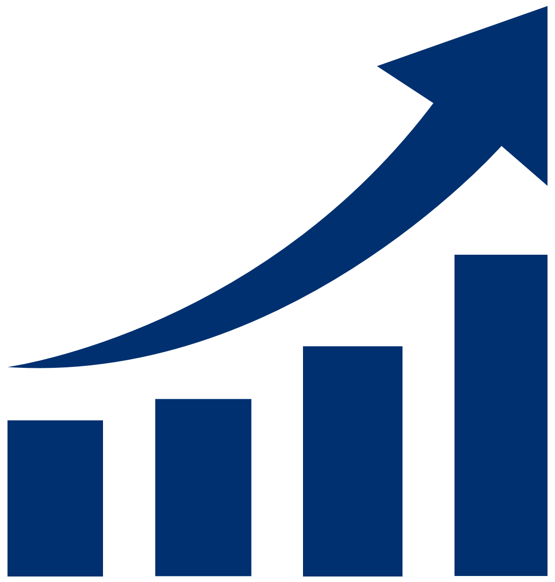


Need and Purpose of the study



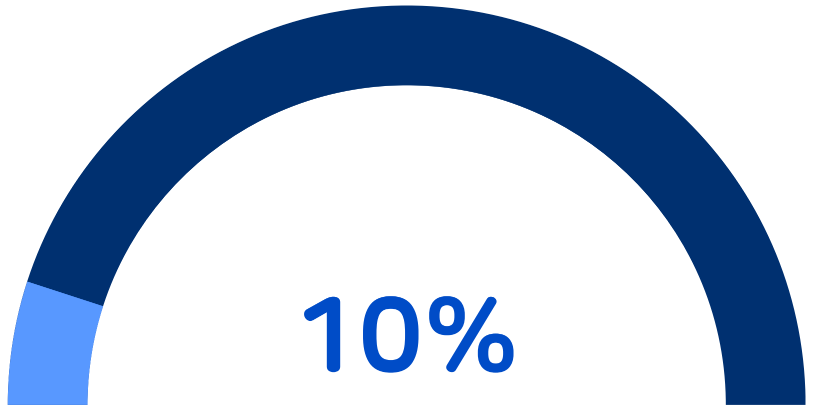
A perfect day has fewer users and lower reuse rates

This is the problem with the perfect day application as envisioned by the Neurons team



Expanded mobile AI recommendation system

Expanded AI recommendation system capabilities to many applications



Lack of research on AI recommendations and usage intentions

While there is research on the relationship between mobile application characteristics and consumer intent to use, there is a lack of research on intent to use with AI recommendation systems

AI Recommendation Service in the literature

To provide suggestions related to various decision-making processes, such as what music to listen to or what online news to read.
In particular, the method of identifying content to recommend according to individual characteristics and tastes to provide personalized services to customers is called “**AI Recommendation System**”.

A study on the factors that affect the intention to continue using AI agent services from a product service system perspective suggested that responsiveness, reliability, variety, and personalization determine the quality of AI agent services.

- 윤성환·임은택·김광용(2019), ‘제품서비스시스템 관점에서의 인공지능 스피커 지속적 사용의도에 관한 연구’, ”글로벌경영학회지 16.5", 73-98면.
- 김상화·오병화·김문종·양지훈·한요섭(2012), ‘협력적 필터링과 콘텐츠 정보를 결합한 영화 추천 알고리즘’, ”정보과학회논문지: 소프트웨어 및 응용“ 39(4), 261-268면.

SERVQUAL in the literature

- Measuring Service Quality - Service Quality

- The SERVQUAL model divides service quality into five dimensions: reliability, empathy, assurance, responsiveness, and tangibility.

- e-SERVQUAL is a consumer evaluation measurement tool for Internet service quality that evolved from SERVQUAL.

- Outcome quality and process quality models propose ways to improve service quality by suggesting antecedent variables that affect each dimension of service quality and outcome variables that are influenced by each dimension of service quality.

- 김문섭·유정헌(2018), '항공사 서비스품질이 고객가치와 태도에 미치는 영향', "한국항공경영학회지" 16(6), 117-136면.
- 이문규(2002), 'e - SERVQUAL - 인터넷 서비스 품질의 소비자 평가 측정 도구', 한국마케팅학회, 73-95면.

Topic Modeling in the literature

- Latent Dirichlet Allocation (LDA) is a probabilistic topic modeling algorithm that uses unsupervised learning to categorize a large number of unstructured documents into topics based on the relevance of words to each other.
- When you write a document, you're organizing it around the topics you want to talk about, so you can determine the percentage of topics in each document and the probability of each topic word.

↓

Use in analytics to extract independent variables based on in-depth interview responses

- Hong, T.-H.·Niu, H.·Ren, G.·Park, J.-Y(2018), 'Multi-Topic Sentiment Analysis using LDA for Online Review', "The Journal of Information Systems" 27(1), 89-110.

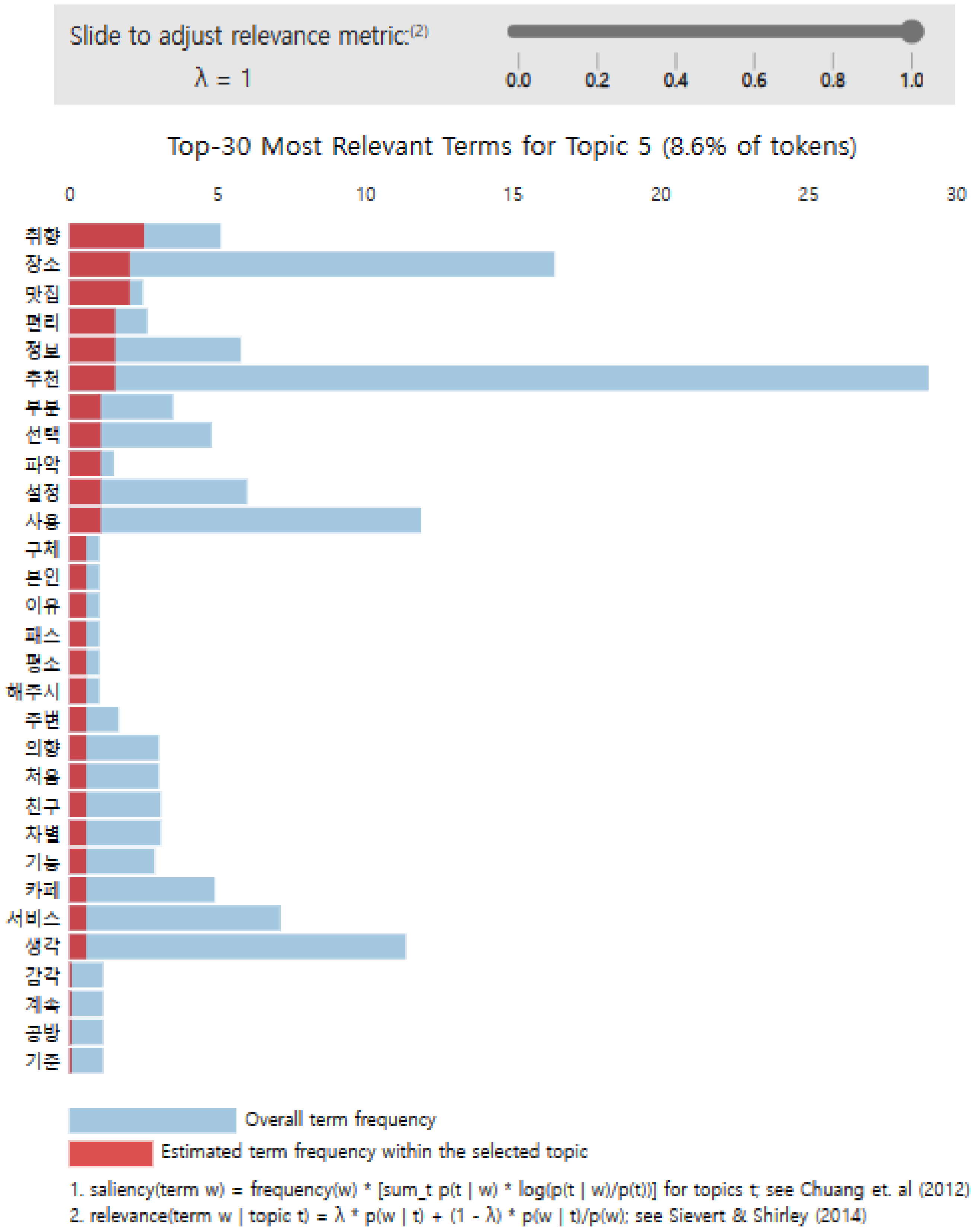
In-depth Interview

- A perfect day for application users
  - Conducted in-depth interviews with seven people (four women and three men)

- Demographic questions and questions specific to AI Recommenders
  → e.g. What makes a perfect day different for AI recommendations?

- Extract four characteristics of AI recommendation services by topic modeling respondents' answers and used them as independent variables

Topic Modeling



Perform topic modeling in Korean

▼

No stopword dictionary for Korean

▼

Extract verb stems and adjectives together

▼

The preprocessing is messy

▼

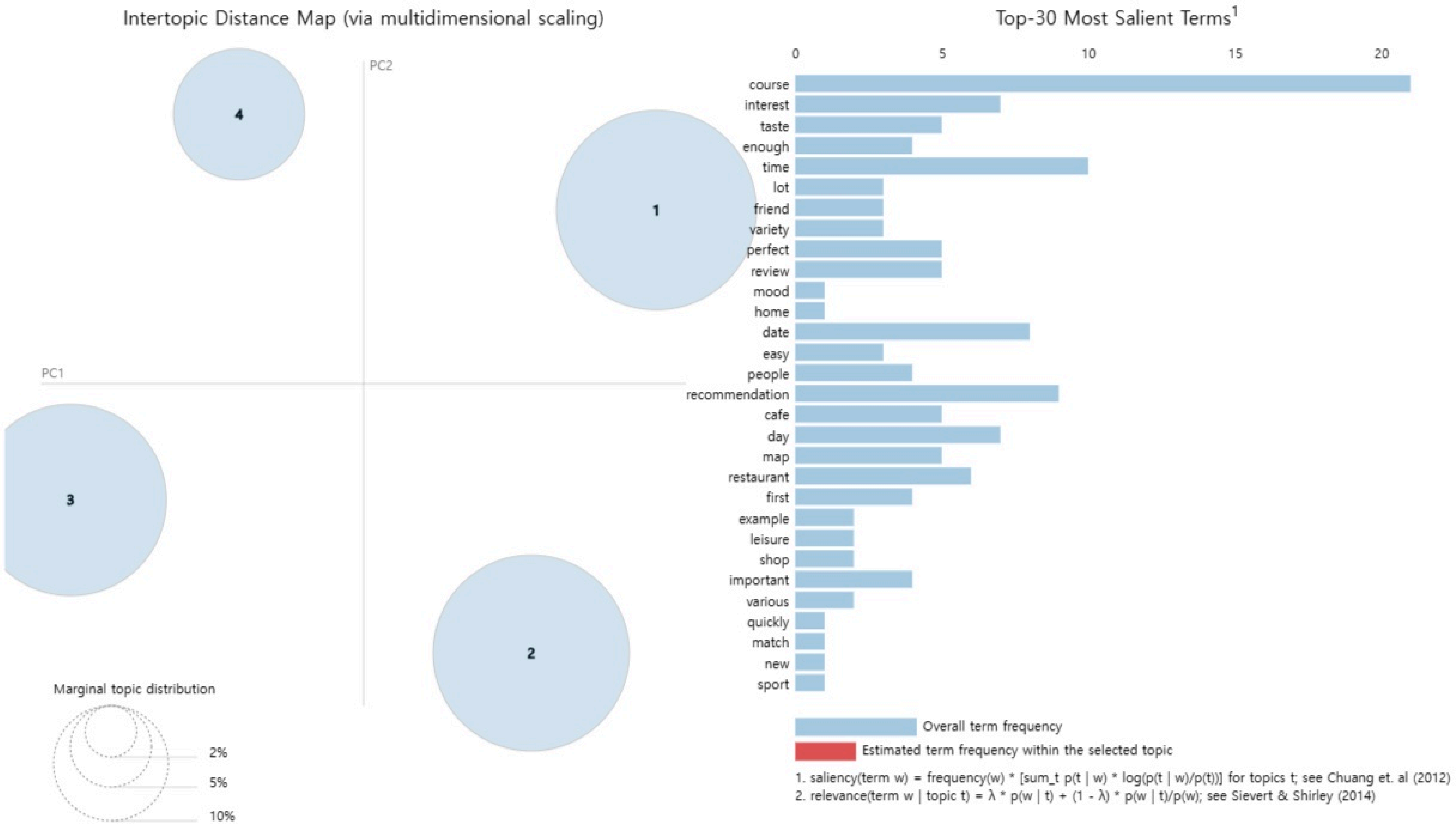
Extract nouns only

▼

Topic classification is not done properly

Topic Modeling

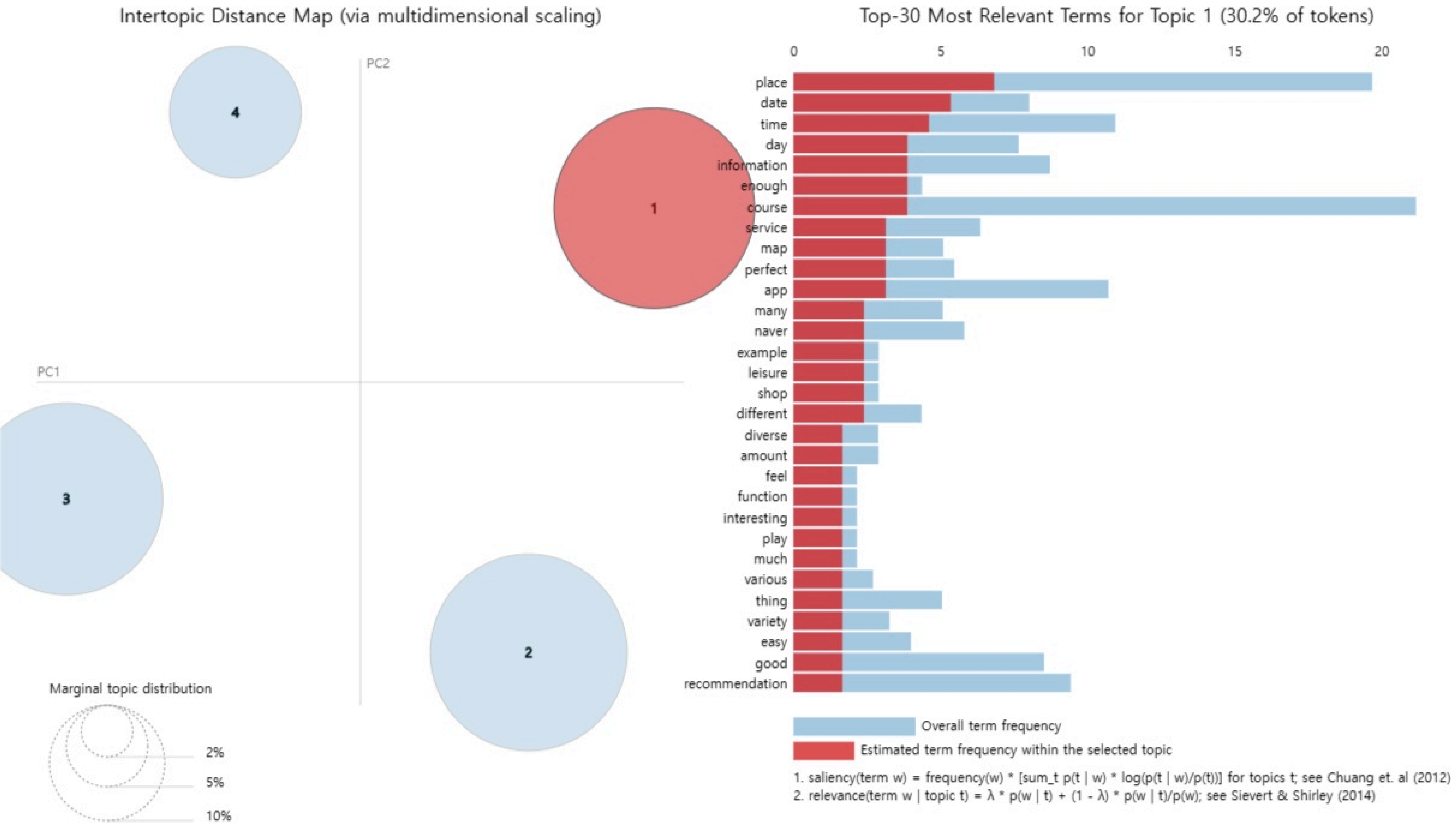
Resolve the issue by performing topic modeling in English, which has a stopword dictionary



Topic 1

Attributes derived from Tangible in SERVQUAL

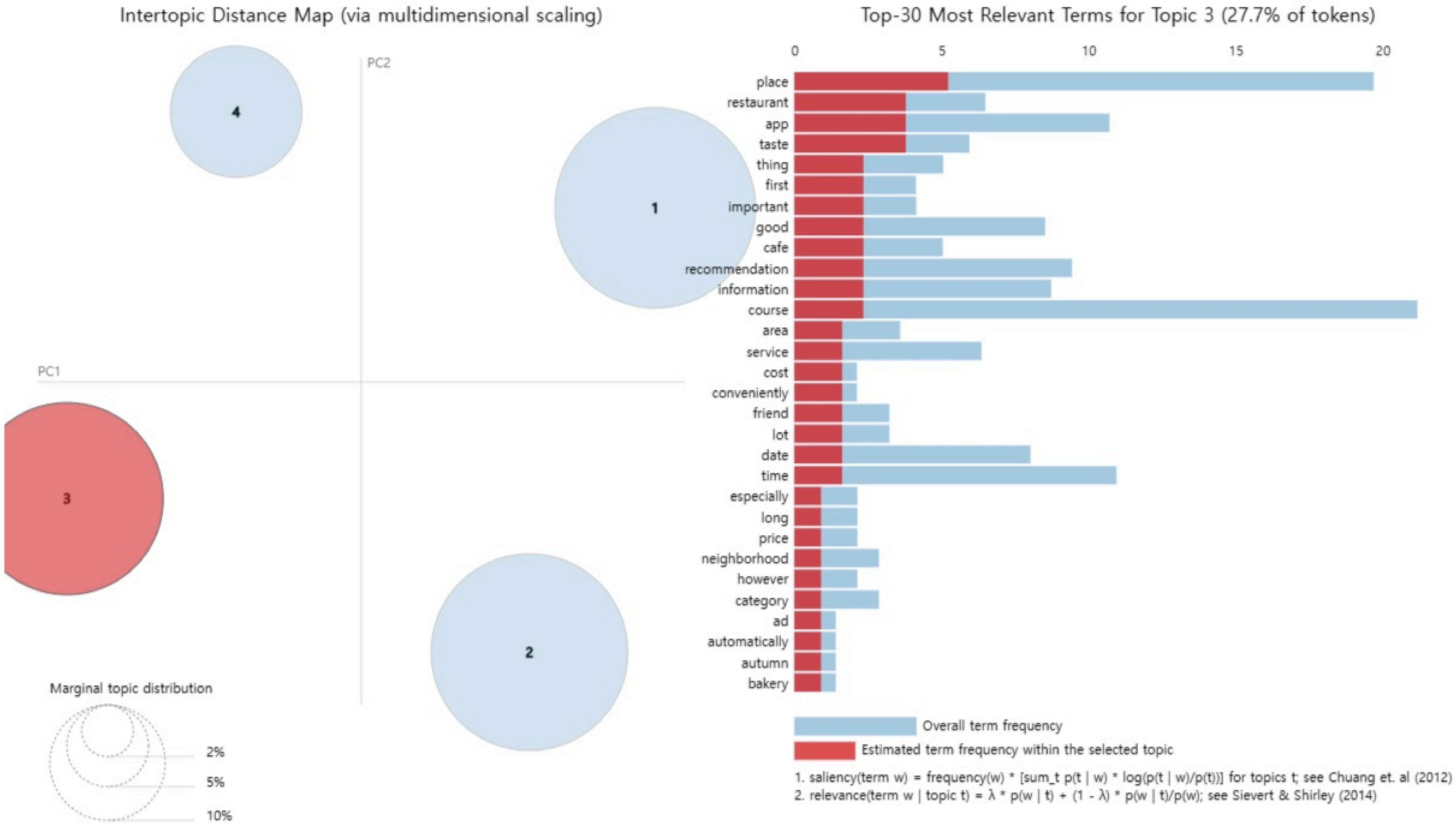
Massive Information Quantity	enough, information, diverse, many, amount, course, various, variety



Topic 2

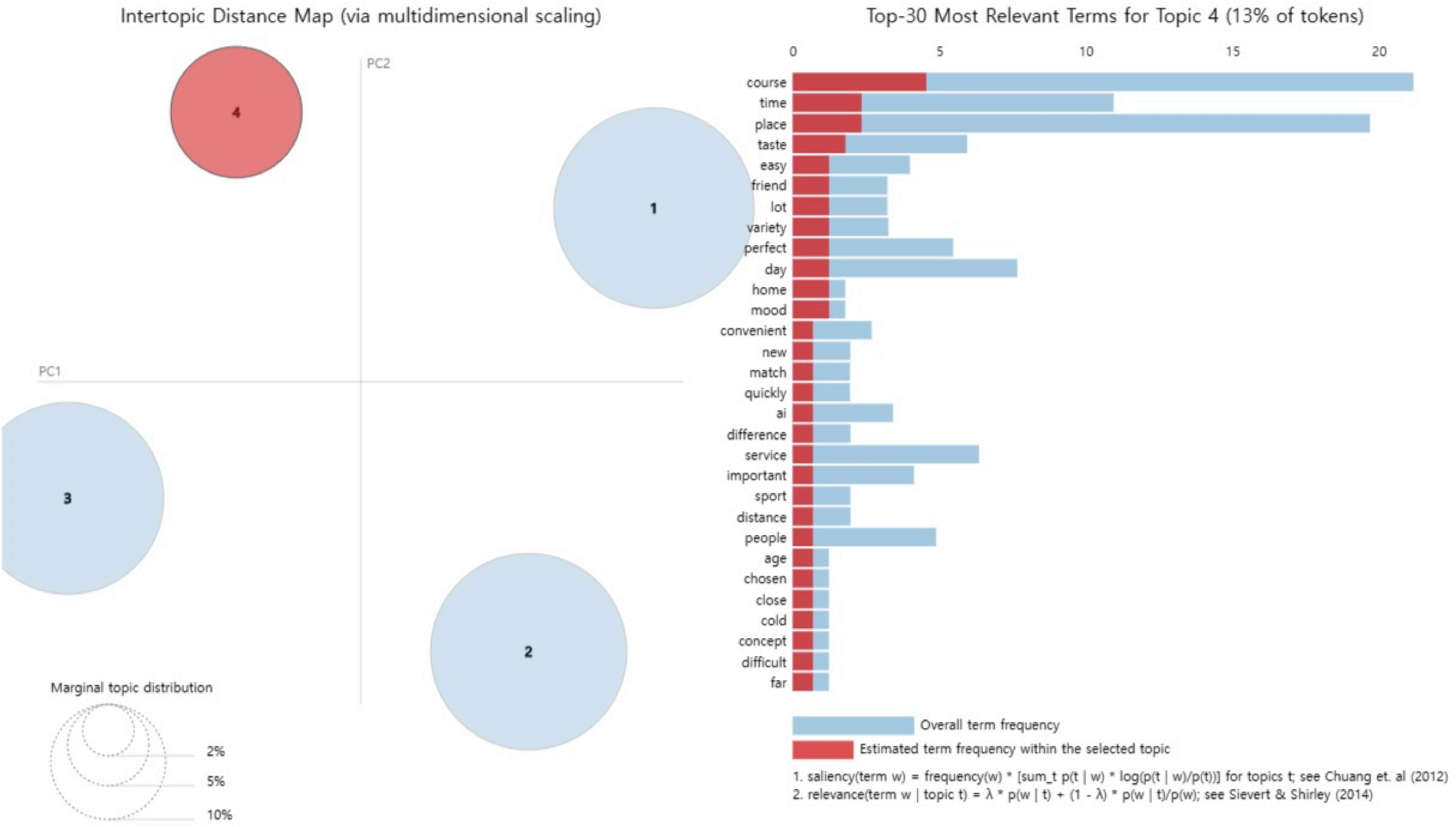
Attributes derived from Assurance in SERVQUAL

Expectation Satisfaction	place, restaurant, app, taste, thing, important, good, cafe, recommendation, course, area, service, cost, conveniently, friend, date, time



Topic 3 Attributes derived from Responsiveness in SERVQUAL

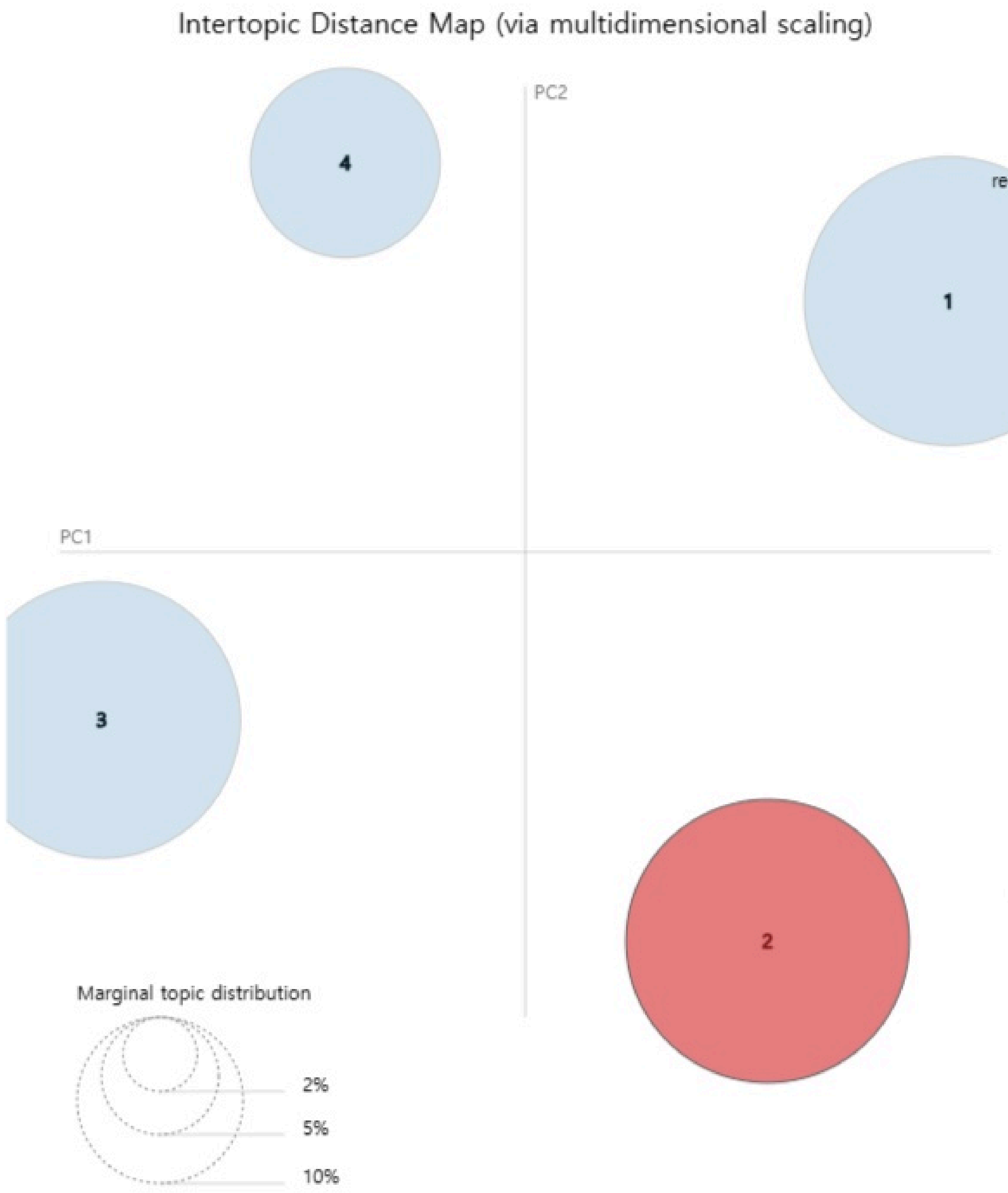
Easiness	time, easy, convenient, quickly, variety

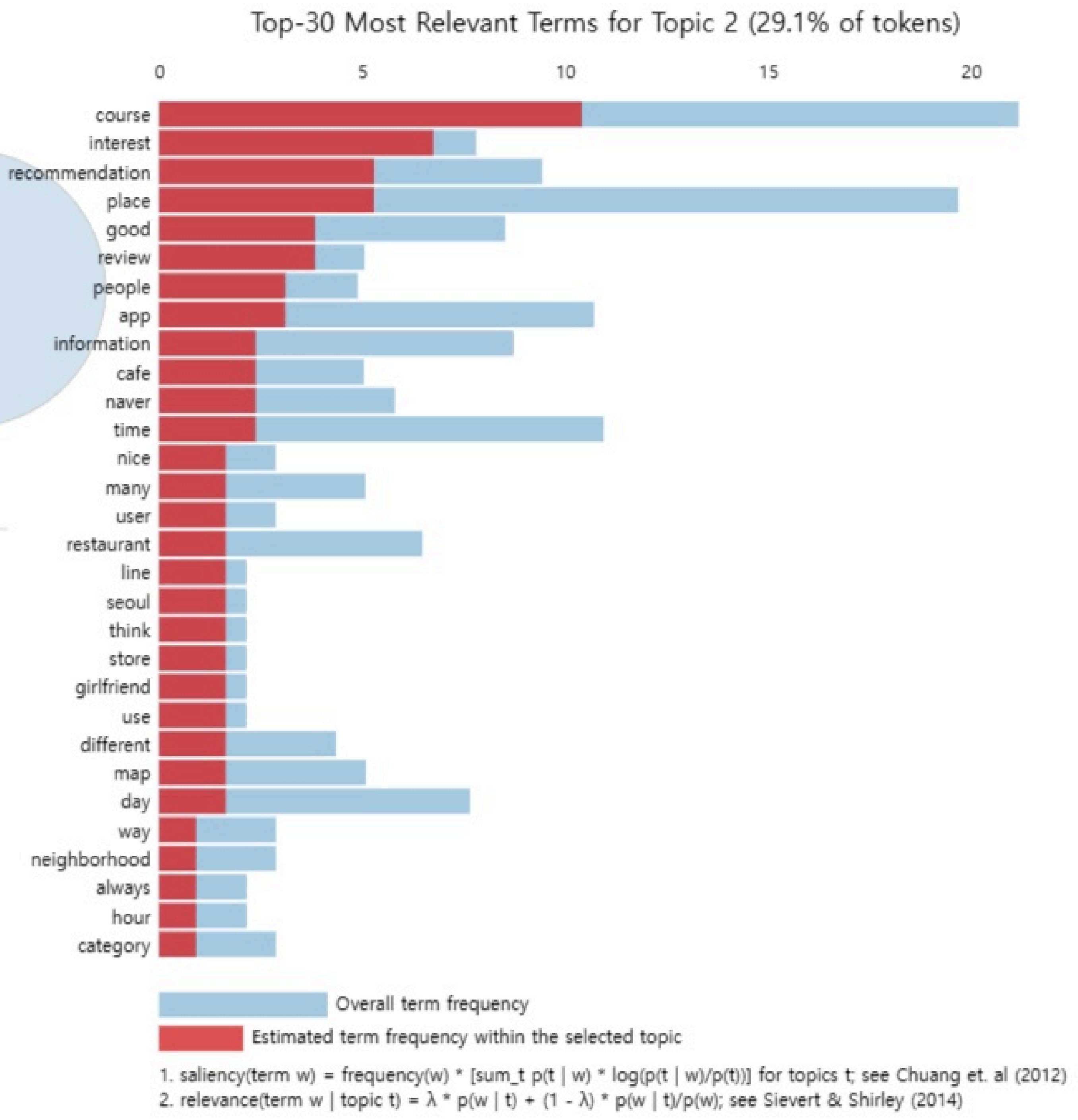


Topic 4

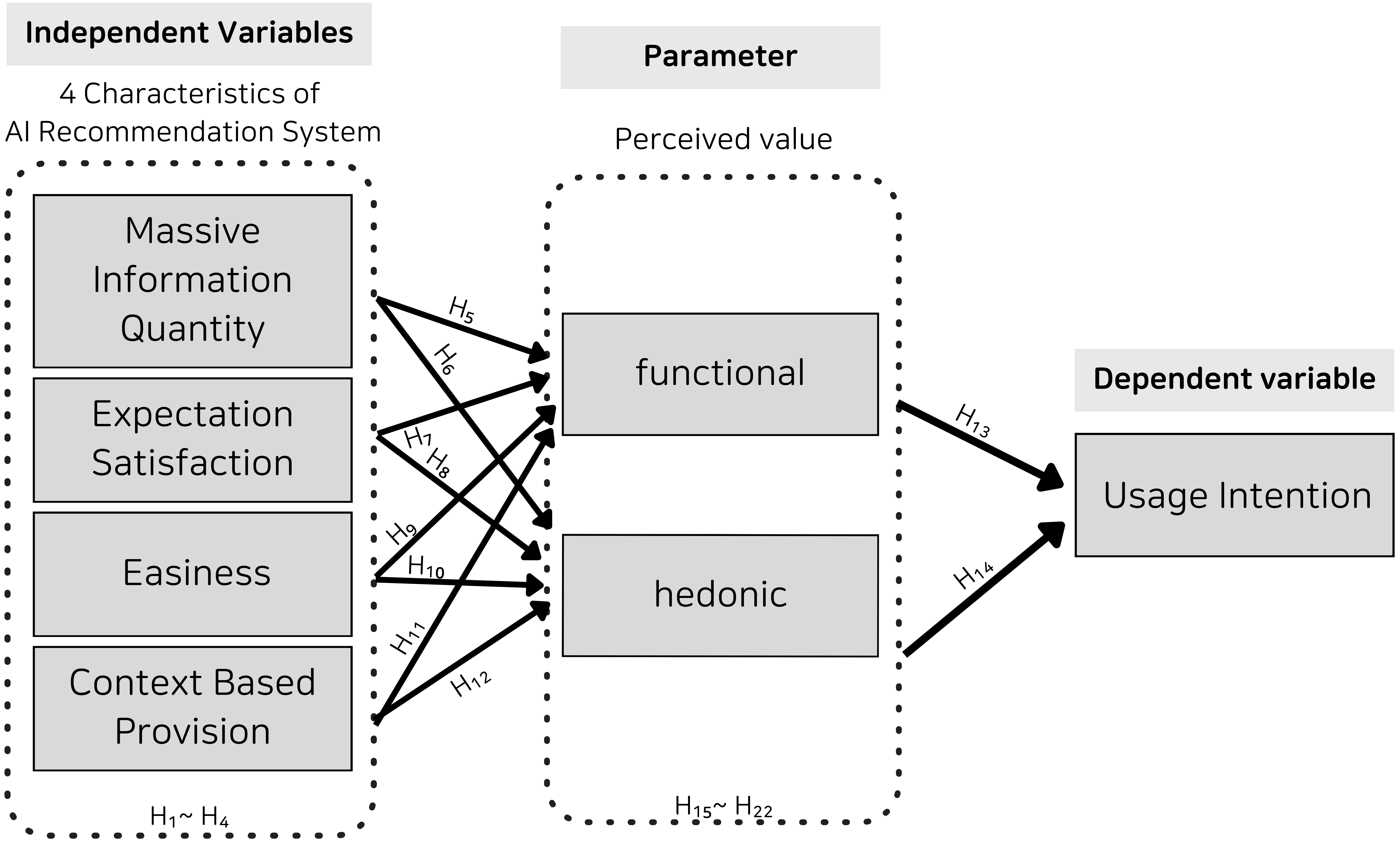
Attributes derived from Empathy in SERVQUAL

Context Based Provision	course, interest, recommendation, place, review, app, information, cafe, time, nice, many, user, restaurant, different, map, day, hour, category





Research models



Research models

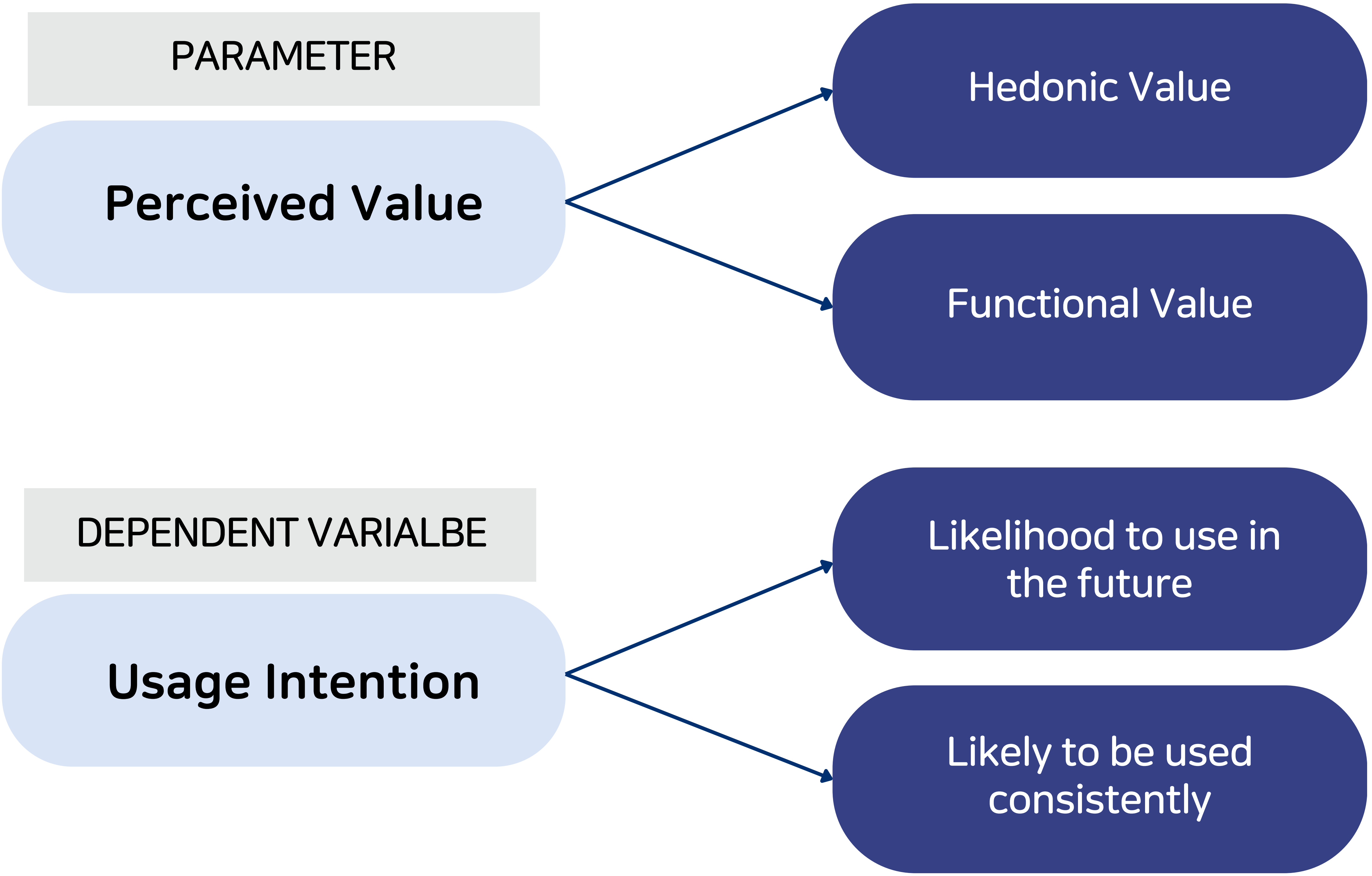
INDEPENDENT VARIABLE

Perfect Day Recommendations System Characteristics

- Conducting in-depth interviews with "perfect day" users
- Conduct topic modeling to extract topics related to traits
- Derived from traits mentioned in servqual prior research papers

Finally, extract four AI recommendation system characteristics

Research models



Hypothesis

Direct Effects

H_1	Massive information quantity has a negative impact on Usage Intention.
H_2	Expectation Satisfaction has a positive impact on Usage Intention.
H_3	Easiness has a positive impact on Usage Intention.
H_4	Context-based provision has a positive impact on Usage Intention.

Independent Variables → Parameters

H_5	Massive information quantity has a negative effect on Functional value.
H_6	Massive information quantity has a negative impact on Hedonic value.
H_7	Expectation satisfaction has a positive impact on Functional value.
H_8	Expectation satisfaction has a positive impact on Hedonic value.
H_9	Easiness has a positive impact on Functional value.
H_{10}	Easiness has a positive impact on Hedonic value.
H_{11}	Context-based provision has a positive impact on Functional value.
H_{12}	Context-based provision has a positive impact on Hedonic value.

Parameters → Dependent Variables

H_{13}	Functional has a positive impact on usage intention.
H_{14}	Hedonic has a positive impact on usage intention.

Mediating effects between independent and dependent variables

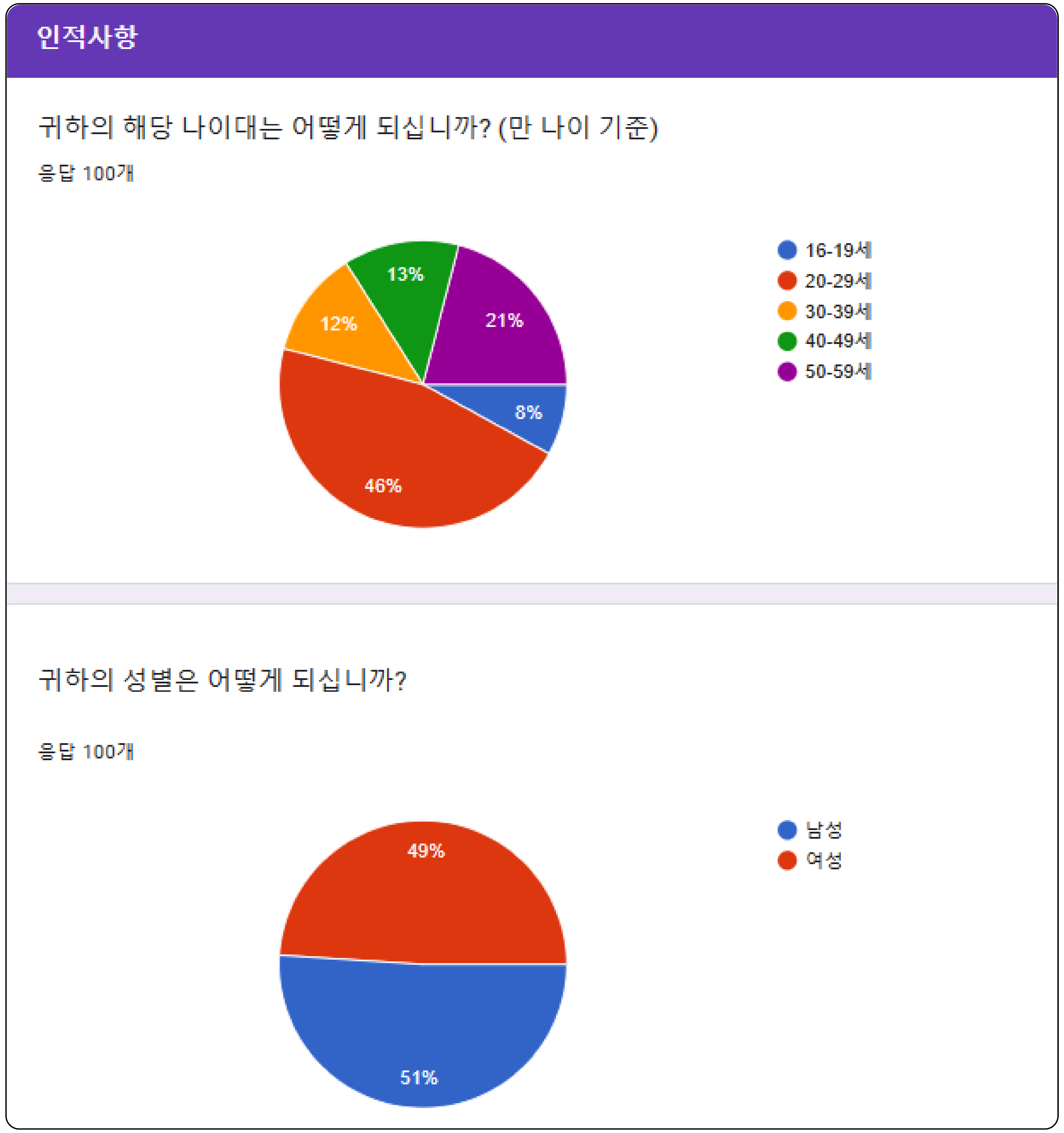
H_{15}	Functional mediates the relationship between Mass Information Quantity and usage intention.
H_{16}	Hedonic mediates the relationship between Mass Information Quantity and usage intention.
H_{17}	Functional mediates the relationship between Expectation satisfaction and usage intention.
H_{18}	Hedonic mediates the relationship between Expectation satisfaction and usage intention.
H_{19}	Functional mediates the relationship between Easiness and usage intention.
H_{20}	Hedonic mediates the relationship between Easiness and usage intention.
H_{21}	Functional mediates the relationship between Context based provision and usage intention.
H_{22}	Hedonic mediates the relationship between Context based provision and usage intention.

Survey

Demographic information	Gender, age range, location, number of people in the household, etc.
Part 1	Research AI recommendation experience and frequency of use
Part 2	Researching perceptions of the volume of information in AI recommendations
Part 3	Investigating whether AI recommendations are tailored to your tastes and perceptions of them
Part 4	Research expectations and perceptions of AI recommendations
Part 5	Researching the convenience and perceived value of AI recommendations
Part 6	Investigate whether AI recommendations provide functional and hedonic value and perceptions of value
Part 7	Continuous usage intent research

Survey

- Surveyed a total of 100 people to test hypotheses
- Age of respondents: 20s with 46% participation
- Male to female ratio: 51:49



JASP-SEM Modeling

Direct effects	Estimate	Std.Error	Z-value	P
Massive Information Quantity → Usage Intention	0.166	0.097	1.708	0.088
Expectaion Satisfaction → Usage Intention	0.073	0.073	1.003	0.316
Easiness → Usage Intention	0.085	0.060	1.419	0.156
Context Based Provision → Usage Intention	0.030	0.037	0.798	0.425

Note. Delta method standard errors, normal theory confidence intervals, ML estimator

Path coefficients	Estimate	Std.Error	Z-value	P
Functional → Usage Intention	0.280	0.102	2.739	0.006
Hedonic → Usage Intention	0.210	0.065	3.221	0.001
Massive Information Quantity → Functional	-0.294	0.107	-2.738	0.006
Expectation Satisfaction → Functional	0.324	0.070	4.666	<.001
Easiness → Functional	0.165	0.065	2.537	0.011
Context Based Provision → Functional	0.033	0.043	0.765	0.444
Massive Information Quantity → Hedonic	0.098	0.168	0.585	0.558
Expectation Satisfaction → Hedonic	0.631	0.109	5.791	<.001
Easiness → Hedonic	0.345	0.102	3.386	<.001
Context Based Provision → Hedonic	-0.081	0.067	-1.195	0.232

Note. Delta method standard errors, normal theory confidence intervals, ML estimator

JASP-SEM Modeling

Total indirect effects	Estimate	Std.Error	Z-value	P
Massive Information Quantity → Usage Intention	-0.061	0.063	-0.976	0.329
Expextation Satisfaction → Usage Intention	0.223	0.055	4.046	<.001
Easiness → Usage Intention	0.119	0.040	2.978	0.003
Context Based Provision → Usage Intention	-0.008	0.023	-0.339	0.735

Total Indirect Effect is the total indirect effect of a specific independent variable on the dependent variable through all parameters.

Indirect effects	Estimate	Std.Error	Z-value	P
Massive Information Quantity → Functional → Usage Intention	-0.082	0.042	-1.936	0.053
Massive Information Quantity → Hedonic → Usage Intention	0.021	0.036	0.576	0.565
Expectation Satisfaction → Functional → Usage Intention	0.091	0.038	2.362	0.018
Expectation Satisfaction → Hedonic → Usage Intention	0.132	0.047	2.815	0.005
Easiness → Functional → Usage Intention	0.046	0.025	1.861	0.063
Easiness → Hedonic → Usage Intention	0.072	0.031	2.334	0.020
Context Based Provision → Functional → Usage Intention	0.009	0.012	0.737	0.461
Context Based Provision → Hedonic → Usage Intention	-0.017	0.015	-1.120	0.263

Indirect Effect refers to the indirect influence of an independent variable on the dependent variable through the parameters functional and hedonic respectively.

Hypothesis validation

H_1	Massive information quantity has a negative impact on Usage Intention.	Not Supported
H_2	Expectation Satisfaction has a positive impact on Usage Intention.	Not Supported
H_3	Easiness has a positive impact on Usage Intention.	Not Supported
H_4	Context-based provision has a positive impact on Usage Intention.	Not Supported

H_5	Massive information quantity has a negative effect on Functional value.	Supported
H_6	Massive information quantity has a negative impact on Hedonic value.	Not Supported
H_7	Expectation satisfaction has a positive impact on Functional value.	Supported
H_8	Expectation satisfaction has a positive impact on Hedonic value.	Supported
H_9	Easiness has a positive impact on Functional value.	Supported
H_{10}	Easiness has a positive impact on Hedonic value.	Supported
H_{11}	Context-based provision has a positive impact on Functional value.	Not Supported
H_{12}	Context-based provision has a positive impact on Hedonic value.	Not Supported

H_{13}	Functional has a positive impact on usage intention.	Supported
H_{14}	Hedonic has a positive impact on usage intention.	Supported

H_{15}	Functional mediates the relationship between Mass Information Quantity and usage intention.	Not Supported
H_{16}	Hedonic mediates the relationship between Mass Information Quantity and usage intention.	Not Supported
H_{17}	Functional mediates the relationship between Expectation satisfaction and usage intention.	Supported
H_{18}	Hedonic mediates the relationship between Expectation satisfaction and usage intention.	Supported
H_{19}	Functional mediates the relationship between Easiness and usage intention.	Not Supported
H_{20}	Hedonic mediates the relationship between Easiness and usage intention.	Supported
H_{21}	Functional mediates the relationship between Context based provision and usage intention.	Not Supported
H_{22}	Hedonic mediates the relationship between Context based provision and usage intention.	Not Supported

Summary

The study conducted in-depth interviews of 30 minutes per person with users of the application on a “perfect day” to extract AI recommendation service characteristics.

Extract four characteristics of AI recommendation services, Massive Information Quantity, Context Based Provision, Expectation Satisfaction, and Easiness, by topic modeling in English based on the results of in-depth interviews.

Hypothesize how each independent variable characteristic affects Functional and Hedonic value to understand its connection to the dependent variable, Usage Intention

Summary

Conducted mediation analysis and path analysis in SEM using JASP to test hypotheses and identify mediating effects

Hypothesis testing revealed that none of the traits had a direct effect on intention to use, but Expectation Satisfaction and Easiness were fully mediated, meaning they had a defining effect on Usage Intention only through perceived value.

In particular, Expectation Satisfaction's relationship with Usage Intention was significantly mediated by both Functional and Hedonic, while Easiness's relationship with Usage Intention was significant only by Hedonic.

Implications

Literature implications

- While there are studies on the relationship between mobile application characteristics and consumers' intention to use, there is a lack of research on the relationship with AI recommendation service systems.
- It is significant that the existing e-SERVQUAL characteristics were extracted and matched through topic modeling based on in-depth interviews with users.

Practical implications

- By conducting in-depth interviews with real users of the application and then extracting the independent variables through topic modeling, we were able to identify the independent variables and characteristics of a substantive AI recommendation service.

- By understanding how independent variables actually affect users' perceived value and usage intentions, the findings can be used to advance AI in a variety of applications and services, not just the "perfect day”.

Limitaions

- Context Based Provision had no effect on perceived value and usage intention, which is different from a previous study that studied context-based provision and perceived value. In that study, context-based provision had a positive effect on perceived value because it provided timely information about personal interests and other news, but in this study, it was not statistically significant because many people felt that AI recommendation services did not provide contextualized services.

- According to the previous research paper, AI recommendation service is defined as a system that collects user information through the system and recommends or provides information that may be of interest to the user. However, the characteristic extracted in this study, Massive Information Quantity, which includes unnecessary information other than the information of interest to the user, was not statistically significant for perceived value and intention to use.

- 기은혜·전현모(2020),'확장된 가치기반수용모델을 적용한 숙박앱의 지속적인 이용의도에 관한 영향요인', "한국호텔관광학회", 214 - 228.
- 유우새·정속영(2023), 'AI 뉴스추천 서비스요인이 사용자의 지속적 사용 의도에 미치는 영향 연구: 기술수용모델을 중심으로', "한국콘텐츠학회", 23(4), 39 - 52면

Limitaions

- According to "Re-examining the Relationship Between Ease of Use and Usefulness for the Net Generation," the research results show that the ease of use of a system does not lead to an increase in intention to use, indicating that ease of use alone may not significantly influence the intention to use AI recommendation services.

- According to "Determinants of College Students' Actual Use of AI-Based Systems: An Extension of the Technology Acceptance Model," research on college students' actual use of AI-based systems shows that while other factors impact attitudes and behavioral intentions, expected satisfaction or attitude towards AI systems does not significantly influence the ultimate intention to use these systems.

- Since the study was based on the 'Perfect Day' AI recommendation service, it was not possible to extract more popular characteristics by considering the characteristics of AI recommendation services in other applications.

- Sheppard, M., Vibert, C. Re-examining the relationship between ease of use and usefulness for the net generation(2019). Educ Inf Technol 24, 3205–3218.
- Kang Li(2023), Determinants of College Students' Actual Use of AI-Based Systems: An Extension of the Technology Acceptance Model, Sustainability, 15(6), 5221

Future research

- We plan to consider the characteristics of AI recommendation services in other applications.
- We plan to use the level of AI recommendation service usage (high/low) as a control variable to gain more interesting insights.
- As AI recommendation services are a hot topic around the world, we would like to study whether cultural differences play a role in AI recommendation services by conducting a survey among Americans. Until now, we have restructured and revised the existing survey into English, resulting in a completed questionnaire. We plan to conduct this survey with approximately 200 American participants through ‘Prolific.’
- The rejected hypotheses will be further explored with quantitative data collected through additional surveys to understand why they were rejected.
- We plan to develop the four characteristics of AI recommendation services derived from SERVQUAL into a service quality tool for AI recommendation services, such as 'AI Recommendation Service-SERVQUAL', and define a new SERVQUAL model in the future.

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Thank You