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Development and Evaluation of a Mobile-based Skincare Recommendation System Using Facial Analysis

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In this paper, we present a mobile application for personalized skincare product recommendations based on facial skin analysis and real-time environmental conditions. The system integrates four core components: a facial detection module for analyzing skin type and acne severity, a cloud database storing product information and user feedback, a personalized product recommendation module, and an environmental adjustment module that incorporates Global Positioning System (GPS)-based location data and weather application program interface (API) to account for temperature, humidity, and ultraviolet (UV) index. The recommendation algorithm considers not only users' skin type and acne conditions, but also other factors including current location, local climate, previous experience, and crowd-sourced ratings, so the product recommendation can be more personalized and accurate. The user interface was validated through eye-tracking experiments to optimize usability for the public. A 54-user pilot test was conducted to evaluate the user experience. The analysis result showed excellent performance in cognitive load, error handling, and information quality, with users appreciating the contextual relevance of recommendations. This application is particularly suitable for young consumers who shop skincare products independently without the help of professional consultation, and it can serve as a valuable tool in retail environments and online shopping platforms. To coordinate with real-time factors, the system has enhanced the ability to provide personalized, location-based recommendations, filling an important gap in existing skincare recommendation technologies.

1. Introduction

The skincare market has evolved significantly in recent years, with cosmetics and skincare no longer being exclusively associated with women. Under the influence of media, streaming platforms, and external cultural factors, users of all genders are paying increased attention to

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their skin conditions. According to Cosmetic Marketing Research Institution (CMRI) Beauty Marketing Research's 2021 report, facial skincare products accounted for over 50% of all cosmetic product categories, with serums, lotions, creams, facial sunscreens, and other products being the most popular items. This diversity of product categories, functions, and items presents a considerable challenge for users attempting to select suitable skincare products.

Traditionally, consumers rely on dermatologists or beauty consultants at medical cosmetic counters to understand their skin condition. For consumers who have no apparent skin issues, it is inconvenient. A more accessible solution that can provide immediate skin analysis and appropriate product recommendations is needed.

In this research, we address these challenges by developing an Android-based mobile application that incorporates facial skin detection capabilities. The application allows users to utilize the device's native camera for facial photography, receive skin condition analysis through face recognition, obtain personalized skincare product recommendations on the basis of analysis results, and access a cloud-based cosmetic product database for real-time recommendations. We also focus on validating the effectiveness of material design principles in the application interface. Is it useful for users' ease of use, and does it increase their attitude toward using the service?

2. Literature Review

2.1 Classification of cosmetic and skin care products and the market

On the basis of Taiwan Food and Drug Administration provisions, cosmetics are categorized into fourteen types.(1) Vu consolidated these into five primary categories: cleansing cosmetics, care cosmetics, color cosmetics, fragrance cosmetics, and special-purpose cosmetics including anti-aging and acne treatment products.(2) In this study, we focus on care and special-purpose cosmetics for recommendations.

According to CMRI's 2021 beauty industry report,(3) facial care products received over 51% of online discussion volume among all cosmetic categories, significantly outperforming body care, makeup, and fragrance products. Among facial care subcategories, serums led consumer discussions with 17.36% share, followed by toners (11.54%) and creams (10.86%). This trend continued in 2022, with serums maintaining 16.72%, toners 11.97%, and creams 9.94% of facial care discussions. On the basis of their consistent market prominence and consumer engagement, we selected serums, toners, and creams as the primary product categories for our cosmetic recommendation software system.

2.2 Recommendation systems

The daily influx of information has been steadily rising, with platforms such as Google Play Store offering millions of applications and YouTube hosting billions of videos.(4) Recommendation systems aim to help users find contents of interest by filtering and recommending information based on user preferences. Common recommendation techniques include content-based filtering, collaborative filtering, and hybrid approaches.(5)

Content-based filtering systems originate from the information retrieval and information filtering fields, primarily recommending items by extracting and analyzing textual information. Examples include website content recommendations, Google advertisements, and product recommendation lists in online shopping.[6] Collaborative filtering, first introduced in 1992 by Goldberg *et al.* through the tapestry system for email classification and management, is considered the origin of collaborative filtering approaches.[7]

Hybrid recommendation systems combine the strengths of content-based and collaborative filtering approaches to mitigate their respective weaknesses and achieve better recommendation quality. Adomavicius and Tuzhilin[6] categorized hybrid methods into four types: implementing collaborative and content-based methods separately and combining predictions, incorporating content-based characteristics into collaborative approaches, incorporating collaborative characteristics into content-based approaches, and constructing general unifying models that incorporate both characteristics.

2.3 Face recognition technology in application systems

Face recognition technology has evolved from fundamental facial contour analysis in the 1960s to sophisticated real-time applications. Unlike fingerprint and iris recognition, it offers noncontact operation and environmental adaptability, with successful implementations in attendance systems and health monitoring.[8]

Modern systems employ Haar-like features or convolutional neural networks for face detection, followed by facial landmark algorithms to identify 68 key points for region-of-interest extraction. Guo *et al.* demonstrated advanced 68-landmark detection techniques and achieved high accuracy in uncontrolled environments,[9] while Hsia *et al.* developed a facial skincare recommendation system using discrete wavelet transform and support vector machines, and achieved 80% consumer satisfaction.[10]

Technical implementations focus on cheek regions, converting RGB images to grayscale for processing. Advanced systems employ DWT-based features for oily skin detection and texture-based features for skin type classification. The HSV color space has been proven effective for brightness normalization and acne detection, whereas random forest classifiers show effectiveness in facial landmark tracking.[9,10]

While face recognition provides the benefit of contactless operation, it faces several challenges. Poor lighting conditions and inconsistent camera quality can affect detection accuracy.[10] However, combining facial analysis with recommendation systems marks an important step forward in skincare technology. It enables objective skin assessment to work in conjunction with a user feedback and recommendation system, leading to tailored product suggestions.

2.4 User experience evaluation for applications

Many measurements have been developed for users' preferences and attitudes. Lee and colleagues[11,12] proposed a comprehensive measurement for evaluating mobile application interface user experience in 2017, consolidating established scales including the System Usability Scale,(13) Questionnaire for User Interface Satisfaction,(14) Post-study System Usability Questionnaire,(15) Website Analysis and Measurement Inventory,(16) Visual Aesthetics of Websites Inventory,(17) Usability Metric for User Experience,(18) and Standardized User Experience Percentile Rank Questionnaire.(19) This measurement incorporates an additional cognitive load dimension, creating a specialized scale for mobile application interfaces and user experience.

The specialized scale evaluates applications across five interconnected dimensions: Visual Aesthetics evaluates interface design, color schemes, and layout attractiveness; Cognitive Load measures ease of use and mental effort required during operation; System Attitude assesses users' overall perception and willingness to continue using the application; Information Quality evaluates consistency, relevance, and usefulness of system-provided information; and Error Resolution measures the system's capability to prevent errors and guide users toward effective solutions. This framework provides comprehensive data for each dimension, enabling developers to promptly improve user experiences with system interfaces.

3. System Analysis and Design

In this section, we introduce the system, including the system architecture, components and interface design. The system functionalities are illustrated in Fig. 1.

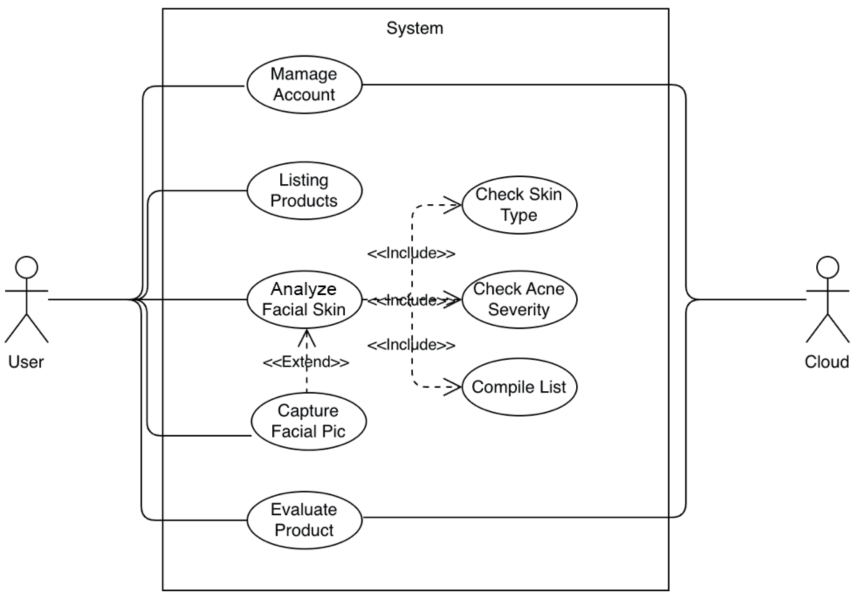

Fig. 1. Use case diagram.

3.1 System architecture

The system comprises two components: a mobile application with face recognition and product recommendation modules (PRMs), and a cloud data module (CDM). The Android-based mobile application allows users to capture facial images using the device's native camera, with two integrated detection modules for skin type analysis and acne severity assessment.

The system workflow begins when users capture facial images through the native camera. Face recognition first verifies valid facial regions, then segments the image according to different facial areas for processing through both detection modules. These results drive the personalized product recommendation process.

Cloud services provide a set of services for real-time data management and storage. The product database on Google Firebase stores comprehensive product information, including brand, volume, origin, name, price, category, and user ratings. This cloud-based approach enables real-time recommendation updates and collects user feedback for system improvements.

The recommendation process integrates detection results and user feedback. The system assigns numerical values to skin types (dry = 3, neutral = 2, oily = 1) and acne severity levels (severe = 3, moderate = 2, low = 1) to facilitate matching algorithms. These values query the cloud database for suitable products, ensuring that recommendations align with users' specific skin conditions.

3.2 Core system components

3.2.1 Face recognition module (FRM)

The system integrates an FRM[9] to verify valid facial features in captured images. Users must grant camera permission to capture photos using the front camera. Upon image detection, the segmentation process divides the facial area into distinct regions, requiring users to retake photos until successful segmentation is achieved. The skin condition classification module categorizes skin type into three levels: dry, neutral, or oily, whereas the acne severity detection module simultaneously evaluates acne levels as severe, moderate, or mild. The matrix of results is coded as Table 1.

3.2.2 CDM

The cloud-based data system manages three data aspects. The user data system includes every user's profile information and skin analysis history. The product information system

Table 1
Skin analysis matrix.

	Acne-mild	Acne-moderate	Acne-severe
Dry skin	Case 1,1	Case 1,2	Case 1,3
Neutral skin	Case 2,1	Case 2,2	Case 2,3
Oily skin	Case 3,1	Case 3,2	Case 3,3

maintains product details, including brand, volume, origin, name, price, skin type preference, custom rating, and product effect. The last system is for rating and feedback. It collects user responses to previously recommended products that can be referred to when making subsequent recommendations.

Users can rate a product on the basis of their personal experience and results. The rate is scaled between 1 and 5. Both rating and counting of rates are essential in the system. Therefore, the score of a product is

$$ProductScore = \sum_{i=1}^{5} Rate_i \times Count_i, \tag{1}$$

where rate is one of the numbers 1 to 5, and Count is the number of every score.

From the total score of one product, the average product score (APS) can be calculated as the *total score/total_rating_count*.

$$APS = ProductScore / total\_ratings \tag{2}$$

$$Normalized\_Product\_Score = APS / 5 \tag{3}$$

The *Normalized_Product_Score* is the normalized APS.

3.2.3 PRM

The PRM operates on a structured product database that categorizes skincare items into three main types: toners, serums, and moisturizers. The matching algorithm combines the dual classification results (skin type and acne severity) to generate nine distinct cases in Table 1. For example, Case (1,1) represents dry skin with low acne severity, whereas Case (3,3) indicates oily skin with high acne severity. The system applies specific recommendation criteria to select suitable products from each category on the basis of these cases.

The PRM calculates the recommendation scores and compiles the proper list of recommendations on the basis of the skin analysis, previous experience, and product information. The current location and weather are also considered.

The PRM utilizes a comprehensive scoring mechanism that considers multiple factors to generate personalized recommendations. The final recommendation score (*frs*) is calculated through a weighted combination of five key components:

$$\begin{aligned} frs = (&w1 * case\_ref + w2 * effect + w3 * userR \\ &+ w4 * env + w5 * Normalized\_Product\_Score)/5 \end{aligned} \tag{4}$$

Each component is processed and normalized as follows.

(1) The skin type and acne severity matching (*case_ref*) indicates the product-user compatibility through dual-factor analysis. Skin type compatibility scores are a perfect match (1.0), an

adjacent type (0.7), and an opposite type (0.3). Acne severity scores are a perfect match (1.0), one-level difference (0.8), and two-level difference (0.5). The final case_ref score is the average of these two matching scores.

(2) The product effect score (*effect*) indicates the alignment between product benefits and user concerns, assigning weights to primary effect matches (1.0), secondary matches (0.7), and additional benefits (0.4). These are weighted and summed for the final effect score.

(3) The user rating factor (*userR*) incorporates personal experience when available. It calculates scores from user ratings and historical consistency. If previous experience does not exist, the system estimates scores on the basis of similar product ratings in the same category.

(4) The environmental adjustment factor (*env*) integrates Global Positioning System (GPS) location data and weather API to retrieve temperature, humidity, and UV index. For temperatures below 20 °C, oil-based moisturizers receive higher scores, low humidity favors hydrating products, and high UV levels prioritize SPF30+ sunscreens with hydration. The *env* factor is weighted to balance with other preferences.

(5) The normalized product score incorporates collective user wisdom by rating quantity and quality, applying time-decay factors to prioritize recent ratings, and maintaining consistency across products with varying review numbers.

Different factors are weighted: skin compatibility ($w1$ = 0.35), effectiveness rating ($w2$ = 0.25), individual user rating ($w3$ = 0.15), environmental factors ($w4$ = 0.10), and crowd wisdom ($w5$ = 0 .15), summing to 1.0 for normalized scoring.

3.2.4 Recommendation algorithm module (RAM)

The RAM provides comprehensive and personalized product suggestions through three main phases: data preprocessing, recommendation generation, and result optimization.

(1) In the data preprocessing phase, all factors for scaling are normalized. User skin analysis results from FRM are converted into numerical vectors representing skin characteristics, while product features from CDM are vectorized for standardized matching. Environmental data is processed into seasonal and geographical indices for contextual awareness.

(2) In the recommendation generation phase, a hybrid approach combines content-based and collaborative filtering techniques. The content-based component utilizes the skin analysis matrix to match products with user characteristics, whereas the collaborative component incorporates user feedback and rating patterns. The algorithm operates through two steps: (i) compiling an initial candidate pool by filtering products matching the user's skin condition and the case_ref matrix from PRM, and (ii) ranking candidates using the frs formula, product effectiveness, user ratings, and environmental compatibility.

(3) In the result optimization phase, the algorithm enhances recommendation quality through diversity enhancement across product categories (toners, serums, moisturizers), novelty factors preventing repetitive recommendations, and seasonal adjustments based on environmental conditions.

The algorithm continuously updates user feedback, recommendation patterns, and product ratings as data is refreshed. This adaptive mechanism ensures that recommendations stay tailored over time.

3.3 Interface design

The system development is based on a user-centered design and prototyping design. Since a user-friendly and easy-to-use interface is a primary factor in users' attitude towards using the interface, Google's material design guideline is employed in the interface design process. We also check the user-eye-focusing area to guarantee a reasonable interface design. The hotspot area of eye-tracking is shown in Fig. 2. The demonstration shows that the primary information attracts users' attention.

4. User Experiments and Results

4.1 User experiment

For the pilot test, we recruited 54 participants to evaluate the application, focusing on young adults who make independent skincare purchasing decisions but may lack extensive product knowledge. The sample consisted of 24 males and 30 females, mostly aged 19–24. These participants typically purchase cosmetics through channels lacking professional beauty advisors, such as retail stores, online platforms, supermarkets, and drugstores. Only 25% of the participants frequented department store beauty counters offering professional guidance, and 74% have prior cosmetics experience. Each participant tested the application individually in a controlled environment with standardized instructions.

Algorithm
Main_Recommendation.

Input:
user_profile, product_database, environment

Output:
ranked_recommendations

```
// Phase 1: Data Preprocessing
normalized_user = NormalizeUserData(user_profile)
normalized_products = NormalizeProductData(product_database)
env_index = ProcessEnvironmentData(environment)

// Phase 2: Generate Initial Recommendations
candidates = []
For each product in normalized_products:
   // Calculate base matching scores
   case_ref = MatchSkinTypeAndAcne(normalized_user, product)
    If case_ref >= THRESHOLD:
        frs = CalculateFinalScore(
            case_ref,              // Skin compatibility
            product.effectiveness,  // Product effect
            user_profile.ratings,   // User ratings
            env_index,              // Environmental factors
            product.crowd_rating    // Crowd wisdom
        )
       candidates.Add({product, frs})
 // Phase 3: Result Optimization
 final_recommendations = OptimizeResults(candidates)
 Return SortByScore(final_recommendations)while budget do
```

Fig. 2. (Color online) Hotspots of eye-tracking experiment.

The above demographic aligns with the study's objective to assist consumers who make independent skincare purchase decisions without professional consultation, specifically targeting younger consumers who shop in self-directed decision-making environments rather than relying on beauty advisors.

4.2 Result

The user experience questionnaire for the application comprises five dimensions: Visual Aesthetics—which evaluates the visual appeal and design quality; Cognitive Load—which measures the mental effort required for interaction; System Attitude—which assesses overall user sentiment toward the system; Information Quality—which examines accuracy and relevance of presented content, and Error Resolution—which evaluates the system's ability to handle and recover from mistakes and is designed using a seven-point Likert scale, in which one means totally disagree and seven means totally agree.

The results for the dimension of Visual Aesthetics are shown in Table 2.

The illustration of the five dimensions is shown in Fig. 3. Most dimensions have users' support for the idea of user experience. The visual aesthetics aspect gets less support because the

Table 2
Users survey results.

Dimension	Mean	Median
Visual aesthetics		
This interface is pleasant.	5.81	6
I like the system's interface.	5.81	6
The layout looks coherent.	5.83	6
The layout feels varied.	5.46	5
The layout is surprising.	5.07	5
The layout makes users feel lively.	5.06	5
The design of the layout attracts me.	5.15	5
The design provides an attractive combination of color in the layout.	5.48	5
The layout is professionally designed.	5.81	6
The layout feels trendy.	5.76	6
The layout is well-designed.	5.78	6
The layout is attractive.	5.39	5
Cognitive load		
The system is easy to use.	5.78	6
The information provided by the system is easy to understand.	5.96	6
The user does not need to learn too many preliminaries before getting started.	6.09	6
No extra help is needed for using the system.	5.98	6
The terms of operation of this site are logical.	5.91	6
The system does not need too much guidance.	5.89	6
It is easy to remember my operation process on the system.	5.87	6
It is easy to navigate in the system.	5.94	6
The system operation has low cognitive load requirements.	5.96	6
Working on the system is not physically demanding.	6.48	7
Users do not feel time pressure while on a task.	6.56	7
No extra efforts are needed to meet the system's operational requirements.	6.46	7
System attitude		
Using this system is not a waste of my time.	5.89	6
This system helps me find what I want.	5.28	5
Overall, I'm happy with the system.	5.50	6
I believe this system is good.	5.56	5
Many things interest me in this system.	5.22	5
I like to use the system.	5.33	5
The information provided by the system is reliable.	5.61	6
I would introduce the system to my friends or colleagues.	5.72	6
I may use the system in the future.	5.50	5
It is a satisfying experience to use this system.	5.65	5
Information quality		
I can quickly learn the new system functions by trying them out several times.	5.20	6
The system's terminology is consistent.	6.30	7
The information position layout is consistent.	6.43	7
The system terminology is relevant to my action.	6.39	7
The words or images on the screen are easily recognizable.	6.41	6
Error resolution		
The error message is helpful.	5.54	6
The error messages directly tell me how to solve the problem.	5.57	6
When I get an error in the operating system, I can recover quickly.	5.87	6
The system provides clear information (e.g., help messages and prompts).	6.24	6.5

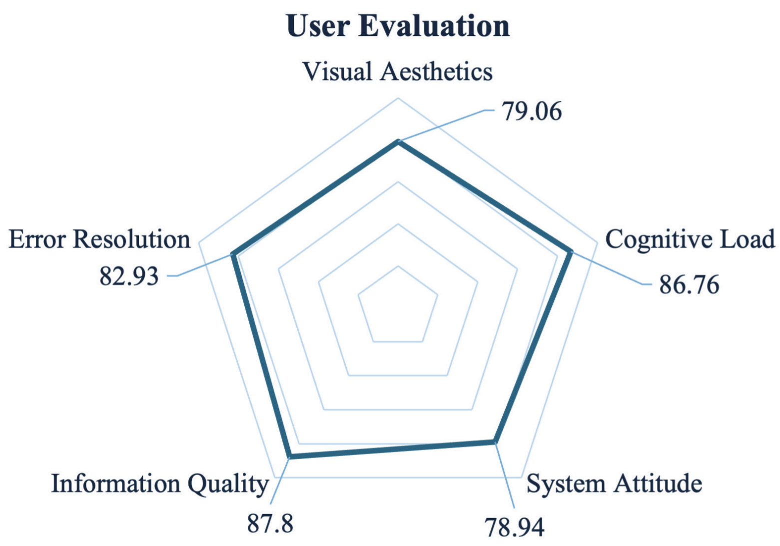

Fig. 3. (Color online) Radar chart for five dimensions.

application is designed as a utility tool for users, and the layout might not be "surprising and attractive" for users. The evaluation of the dimension of system attitude is also lower than the average, especially for those users who have more experience in cosmetics shopping.

5. Conclusions

In this paper, we presented a comprehensive mobile-based skincare recommendation system that addresses the growing need for personalized product selection in the digital beauty market, with three key contributions: (1) an integrated system architecture combining facial detection and cloud services, (2) a 3 × 3 matrix recommendation system considering skin type, acne severity, and environmental factors, and (3) a location-based adaptive recommendation model leveraging GPS and weather data such as temperature, humidity, and UV index.

Because of utilizing material design concepts on the user interface, users' feedback generated exceptional results across all evaluation dimensions, confirming the system's effectiveness for young shoppers. While this study was focused on participants aged 19–24, future research should be expanded to broader age groups and diverse demographics. Integrating a cost-effective portable skin-sensing device could be another extension, enabling more accurate recommendations.

In summary, the integration of environmental factors and personal analysis provides significant value for users, and addresses real-world shopping scenarios where professional guidance is unavailable.

References

1 Ministry of Health and Welfare: Cosmetic Hygiene and Safety Act (amended May 2, 2018) https://law.moj.gov.tw/LawClass/LawAll.aspx?pcode=l0030013 (accessed December 2024).
2 T. L. Vu: The Influence of Factors on the Purchase Intention of Cosmetics – The Case Study of Vietnam and Taiwan, Master's thesis, National Taipei University of Education (2020). https://hdl.handle.net/11296/795nqb
3 CMRI: CMRI COSMETICS INSIGHTS (published January 23, 2022) https://cmri.itrue.com.tw/2022/01/23/2021yearlyanalysis/ (accessed December 2024).
4 Google, "Recommendations: What and Why? | Recommendation Systems," Google Developers. https://developers.google.com/machine-learning/recommendation/overview (accessed December 2024).
5 C. H. Huang: Art Enthusiast, A Case of Recommender System Application Using Open Government Data, Master's thesis, National Taipei University of Education (2015). https://hdl.handle.net/11296/bf467e
6 G. Adomavicius and A. Tuzhilin: IEEE Trans. Knowl. Data Eng. **17** (2005) 734. https://doi.org/10.1109/tkde.2005.99.
7 D. Goldberg, D. Nichols, B. M. Oki, and D. Terry: Commun. ACM **35** (1992) 61. https://doi.org/10.1145/138859.138867
8 M. C. Huang, I. P. Chen, H. L. Huang, S. F. Sung, and A. G. Wang: Sens. Mater. **33** (2021) 1787. https://doi.org/10.18494/SAM.2021.3203
9 J. M. Guo, C. H. Hsia, L. W. Hsiao, and C. C. Yao: J. Inf. Sci. Eng. **37** (2021) 793. https://doi.org/10.6688/JISE.202107_37(4).0004
10 C. H. Hsia, T. Y. Lin, J. L. Lin, H. Prasetyo, S. L. Chen, and H. W. Tseng: Sens. Mater. **32** (2020) 3235. https://doi.org/10.18494/SAM.2020.2862
11 T. L. Lee: User Experience of Mobile Application's Interface: Measurement Development, Master's thesis, National University of Kaohsiung (2017). https://hdl.handle.net/11296/2v4f5v
12 S. C. Yang, T. L. Lee, and T. T. Feng: Proc. 5th Multidisciplinary International Social Networks Conf. (ACM, 2018) 1–5. https://doi.org/10.1145/3227696.3227698
13 J. Brooke: SUS: A 'Quick and Dirty' Usability Scale, P. W. Jordan, B. Thomas, I. L. McClelland, and B. Weerdmeester, Eds. (CRC Press, 1996) pp. 189–194. https://doi.org/10.1201/9781498710411
14 J. P. Chin, V. A. Diehl, and K. L. Norman: Proc. SIGCHI Conf. Human Factors in Computing Systems (1988) 213–218. https://doi.org/10.1145/57167.57203
15 J. R. Lewis: Proc. Human Factors Society Annual Meeting (1992) 1259–1263.
16 J. Kirakowski and B. Cierlik: Proc. Human Factors and Ergonomics Society Annual Meeting **42** (1998) 424–428. https://doi.org/10.1177/154193129804200400
17 K. Finstad: Interact. Comput. **22** (2010) 323. https://doi.org/10.1016/j.intcom.2010.04.004
18 M. Moshagen and M. T. Thielsch: Int. J. Hum. Comput. Stud. **68** (2010) 689. https://doi.org/10.1016/j.ijhcs.2010.05.006
19 J. Sauro: J. Usability Stud. **10** (2015) 68. https://uxpajournal.org/supr-q-a-comprehensive-measure-of-the-quality-of-the-website-user-experience/