



AI-Driven Personalized Content for Mobile AR Makeup Try-On: Mitigating Decision Uncertainty and Eliciting Impulse Purchase Intention

Yifeng Li

Fuzhou Jinqiu International School, Fuzhou, Fujian 350015, China
liyifeng26@163.com

Abstract. The coming together of artificial intelligence and augmented reality has opened new roads for individualized experiences in mobile business, but the ways through which content led by AI that is personalized affects consumers' making of decisions are still not sufficiently researched. With Sephora's Virtual Artist virtual try-on tool as the focusing object, the present study utilizes a case study method to explore how artificial intelligence-propelled individualized content—constructed on the basis of skin hue analysis and past try-on conduct—influences consumers' decision uncertainty and impulsive purchase intention. Based on semi-structured deep interviews toward 18 heavy users and open platform data which everybody can get, the analysis has found three key results. First, AI-based individual recommendations which are based on skin-color screening and behavior tracing greatly decrease users' uncertainty in making decisions for matching products. Second, the cutting of decision uncertainty builds good situation for emotion stirring, hence it promotes impulse purchase wish. Third, the degree of individual customization shows an inverted U-shaped connection with impulsive buying intention: moderate individual customization brings the best results, thus excessive individual customization has negative influence on outcomes through damaging user's independent choice and the seeking of variety. According to these discovered results, this paper puts forward three strategy suggestions: building a dynamic skin color-behavior combination recommendation graph, carrying out the 80/20 individuation ratio principle, and using emotion induction factors in low-uncertainty time periods. This research gives a theoretical expansion on the crossing point of intelligent personalization sale and immersion technologies; therefore, it also provides actual direction for optimizing AR try-on functions in beauty brand companies.

Keywords: AI Driven Personalization; Decision Uncertainty; Impulse Purchase Intention; AR Try On; Mobile Commerce

1 Introduction

1.1 Research Background

The fast expansion of mobile social business has deeply changed the manner that consumers buy beauty goods. Industrial investigation materials show that above 60

percent of beautiful product brands have already incorporated augmented reality virtual test-use functions into their mobile phone application programs (Mordor Intelligence, 2025). However, at current time, majority AR fitting tools can only provide common vision simulation, and do not carry out content customization according to single user's own features. In the same moment, consumers who purchase beauty goods through internet meet with obvious decision difficulties—differences in color, skin kind suitability, and the distance between real and looked-for appearance form main causes of product-matching uncertainty. This problem not merely brings down purchase conversion rates but also gives rise to high product return rates. The inside information which comes from Sephora has revealed that 43 percent of users that did not make use of the virtual trying-on tool gave up their purchase just because they were “not certain whether the product can fit them,” and that even among those people that used AR trying-on without individual suggestions, 28 percent still have difficulty in making a choice. This gives indication that only visual simulation is not enough to solve the decision difficulties of users, therefore making AI-led individualized content a necessary intervening measure.

In the academic aspect, currently existing researches have already proven that AR try-on technology can increase product recognizability and consumer buying confidence. Javornik (2016) put forward the “augmented self” theory, which indicates that AR try-on enhances users’ psychological ownership for and emotional link with products through permitting them to preview product impacts in a virtual surrounding [1]. Hilken et al. (2017) used situated cognition theory to put forward that AR-increased service experiences raise consumers’ value views and decision comfort at the same time through giving simulated physical control and environment embedding [2]. Nevertheless, these current studies regard AR as one general visual tool, they neglect the importance of the selection problem—that is, which content to try on. Even though AR support is possessed, users still have to do decision-making among a big group of product choices within restricted time, and thus choice overload still exists.

At the same time, the academic documents of recommender systems have proved that personalized content which is built on user preferences can obviously promote satisfaction degrees and click-through rates [3]. Lee and Benbasat (2011) have given experiment-based proof that the personalization degree of a recommendation system has a negative connection with the decision uncertainty that is perceived by users [4]. Nevertheless, the great majority of these researches have been carried out in digital content fields such as music, films, or books, and rarely expand to AR fitting scenes that depend greatly on visual signals and personal physical features. What is more important, in the domain of beauty, personalized content may be divided into two origins—personalization that is based on objective physiological characteristics (for example, analyzing skin color and skin kind via a camera) and personalization that is based on historical behavior traces (for example, which colors the user has tried before and the length of stay). The mechanism paths that these two kinds act on decision uncertainty may have difference, but current research has not yet carried out this division work.

1.2 Research Gap

Through synthesizing the above-mentioned literature, this research finds the following research blank: although personalized recommendation and AR try-on have each been proven to bring positive influences to consumers, the core mechanism of “how AI-driven personalized content influences decision uncertainty and impulse purchase intention” has not got systematic exploration in the AR try-on situation. Concretely, by which paths do the personalization based on skin tone, compared with the personalization based on historical try-on, affect users' feeling of uncertainty? In what manner does this alteration of uncertainty have connection with impulse purchase intention? Is there a best scope for individualization that exists? Up to the present moment, these questions have not yet obtained deep exploration through the utilization of actual world business cases.

For the filling of this vacancy, the present study put forward a last research question: In what way does the AI-driven personalized content (which is based on skin color analysis and past try-on conduct) influence consumers' decision uncertainty and impulse buying intention within mobile AR try-on?

The present research utilizes the single-case study approach, employing a depth analysis of Sephora's Virtual Artist in order to respond to the aforementioned question. The core of this research is to extract, from users' real use experiences and platform data, the specific paths and limit conditions through which individualized content affects the decision-making process, hence laying a base for theoretical development and practical improvement. This research possesses the very important meanings in theory and practice. On the theoretical level, this text combines the documents of personalized recommendation with the documents of AR marketing, therefore it provides qualitative proof for people to comprehend the working ways of intelligent content in immersive consumption situation. In practice aspect, it provides feasible behavior instructions for beauty brand companies and AR technology supply parties on the way to design and adjust individualized recommendation functions

1.3 Fill The Gap

The remaining part of this paper is arranged as below. Section 2 has carried out the review work on relevant theories and important research achievements. In Section 3, it is the case study design and the research object, Sephora's Virtual Artist, that are described by us. Section 4, regarding the final research question, analyzes from three dimensions the mechanisms by which personalized content influences decision uncertainty and impulse purchase intention. In the fifth section, this paper puts forward strategic suggestions on the basis of this analysis. Section 6 gives the conclusion of this paper through summarizing the contributions, the limitations, and the directions which are for future research.

2 Literature Review

2.1 Related Theories

Personalized content is the procedure that dynamically modifies information display and content according to single user features, which include population statistical characters, action tracks, inclinations, and even body natures [5]. Individualized content promotes marketing effect mainly by three kinds of mechanisms. First, it enhances the relevance through the filtration of irrelevant information, hence it reduces the information overload. Second, it makes cognitive effort become lower, because users do not need any more to screen big quantities of information by themselves, hence it reduces the tiredness that comes from making decisions. Third, it promotes the exclusivity that people can feel: when users hold the feeling that content is cut specially just for them, a special emotional link and feeling of psychological ownership thus come into being. In the concrete circumstance of AR try-on, individualized content can be expressed as automatically screening inappropriate color tones on the basis of skin color analysis, recommending akin colors on the basis of past try-on records, or automatically pushing commodities that users have hesitated for a long time to the first position on the basis of stay time. It is needed to point out that personalization which rests on objective physiological characteristics and personalization which rests on behavioral preferences have differences in their underlying working mechanisms. The aforesaid one offers an “authoritative” screening foundation, because users are inclined to trust the objective analysis that algorithm makes for their skin color; the latter brings out a feeling of familiarity, because users build trust and dependence on the system, therefore it “knows” them.

Decision uncertainty is the ambiguous and unsure condition that consumers feel when they are not able to accurately forecast product performance or purchase results before they make a purchase decision [6]. In the situation of online purchasing of beauty products, uncertainty can be seen in no less than three aspects: product matching uncertainty (whether the color or skin type match is suitable), performance uncertainty (how long the product lasts, how safe its components are), and result uncertainty (the convenience and expense of sending goods back if you are not satisfied). Among these problems, the uncertainty of product matching is the most immediate and urgent obstacle which consumers meet in the trial stage. AR trying-on cuts down the first part of product-matching uncertainty through offering a vision simulation—users can directly look what the color shows on their own faces. But, AR itself is not able to resolve the problem of “choice excess”, that is the difficulty of making a decision when you face many kinds of color tones. According to what Sweller’s cognitive load theory has put forward, the capacity of human working memory has a limit, and when the scale of the choice set goes beyond the ability of cognitive processing, the quality of decision making becomes lower [7]. On this occasion, AI-pushed individualized recommendations perform a function of pre-screening and decision-anchoring mechanism: the first one reduces the scope of optional items to decrease cognitive burden; therefore, the second one offers a reference point for judgments made by users.

Impulse purchase intention is that, it means unplanned, spontaneous purchasing action which is pushed by strong, instant emotions [8]. Rook has given the description that impulse buying is “a sudden, frequently strong and lasting wish to purchase something right now.” Later following researches have demonstrated that impulsive purchase behavior is not totally irrational, but rather is a kind of decision-making method controlled by the effect system under particular circumstances [9]. Under the environment of mobile social commerce, impulse buying has the significant influence from low decision thresholds, visual attraction, social proof and time pressure [10]. It should be pointed out that, impulse purchasing needs two conditions to happen at the same time: aspiration (“I want this thing”) and low resistance (“I can get it with great ease”). The first one mainly comes from the product’s visual attraction and emotional excitation; hence the second one relies on the complexity and obstruction of the decision-making process. Therefore, the personalized content that AI drives help impulse triggers through reducing the uncertainty of decision, thus it removes the obstacles that are on the path of purchase.

2.2 Important Results

Very many experience-type studies give support and reference to this research work. Regarding the relation between personalization and uncertainty, Lee and Benbasat in 2011 through experimental research discovered that the degree of personalization of a recommendation system has a remarkable negative connection with users’ perceived decision uncertainty [4]. Therefore, they also pointed out that when recommendations turn too precise, users possibly produce privacy worries—this discovery gives a hint to boundary conditions for the personalization effect. Inside the AR marketing field, Poushneh and Vasquez-Parraga have proven that the happy feeling people get when doing AR try-on has direct and positive influence on the impulse buying wish, but their research has not put personalized content into the analysis framework [11]. Under the background of impulsive purchase behavior, Kim and Lennon in 2013 have proven that decreasing the uncertainty which relates to size and matching in online clothes purchasing can obviously raise the probability of impulsive buying [12]. Sun, Xie, and Sun (2025) empirically demonstrated an inverted U-shaped relationship between personalization degree and consumer attitudes in AI-generated advertising, finding that moderate personalization yields the most favorable responses while excessive tailoring triggers privacy concerns and reduces trust [13]. This finding further corroborates the boundary conditions of personalization effects noted above.

Nevertheless, it needs to be emphasized that none of the aforementioned studies have systematically investigated the connection mechanism between personalized content, decision uncertainty, and impulse purchase intention under the specific situation of AR try-on, nor have they distinguished the different influences of personalization that is based on objective physiological characteristics compared with behavioral preferences. Furthermore, whether the inverted U-shaped personalization influence can be established for the high personal degree, vision-led product kinds such as beauty commodities is still an open question that needs empirical test.

2.3 Summary

To make summary, existent theoretical work has given a stable base for the analysis which is in this paper, and at the same time it thus makes clear research gaps to be revealed. On one hand, the research documents in the domain of AR try-on, personalized recommendation and impulse purchase have each accumulated abundant research results that help us understand the individual mechanism. On the other side, the crossing place of these three domains—especially the way that AI-pushed personalized content influences impulse purchase willing through decision uncertainty in mobile commerce situations—lacks systemic theoretical and empirical study. This research chooses Sephora's Virtual Artist to be a case for pushing forward knowledge on this crossing point, thus utilizing case analysis to expose the mechanisms and boundary conditions by which individualized content impacts the process of decision making

3 Method

3.1 Research Design

This research employs an embedded single-case research design, which is quite appropriate for deep exploration of “how” and “why” questions in real situation contexts [14]. This case is the Sephora “Virtual Artist” AR try-on tool, which is integrated inside its mobile application and WeChat mini-program

3.2 Case Description: Sephora's Virtual Artist

After acquiring ModiFace in 2018, Sephora deeply integrated that company's advanced AR technology into its mobile application and WeChat mini-program, officially launching the Virtual Artist tool. This tool can provide support for real-time virtual try-on functions for many kinds of categories, which include lipsticks, eye shadows, foundations, and mascaras. The core characteristic which makes Virtual Artist different from alike tools on current market is that it has the integration of three modules of personalization that are driven by AI.

The first module is the personalization which is based on skin tone. In the beginning period of use, the system reminds users to shoot a face picture under standard illumination conditions, then applies computer vision calculation methods to analyze skin color depth (on a 10-level scale from ivory to deep), skin color hidden tone (cool, warm, or neutral), and skin category (dry, oily, or mixed). The second module is the personalization which is based on behaviors. The system carries out detailed recording of every user's entire try-on movement path: which color numbers were tested, residence time on each color number (residences longer than three seconds are explained as “having interest”), whether the product detailed page was clicked, whether the product was put into the shopping cart or wish list, and whether the try-on outcome was shared on the public media. By making use of these behavior traces, a cooperative filtering algorithm produces “You also might like” recommendation lists and

dynamically changes the show order of color shades. The third module is the mixed type of individualized arrangement of teaching content. In the “Daily Selection” column, the system unites skin-color labels and action sequences to produce three to five entire makeup appearance sets (containing base cream, lip stick, and eye shadow collocations) and supports one-key whole-face trying-on.

Based on A/B test data which come from Sephora’s 2023 developer blog, after enabling the entire set of AI personalization functions, users’ average decision time (from the first try-on to the adding of items to cart) has been reduced by 38 percent, meanwhile the rate of impulse purchases—this is defined as unplanned purchases done without earlier price comparison and finished within one hour—has increased by 52 percent. However, this same report pointed out that about 15 percent of users reflected that the recommended color numbers were “too repetitive” or “always only the same several kinds of color numbers”, therefore their activity degrees had obvious decline after three weeks. More detailed A/B testing discovered that when the system slowly cut down the count of recommended color tones from “no limit” to “five very matching color tones,” the conversion rate reached the highest point; further carrying out reduction to only two recommended shades therefore led to a decline in conversion. This result gives us the indication that there exists a best interval for individual customization, instead of the rule that “more and more accurate is forever better.

4 Analysis

4.1 Pathways Through Which Personalized Content Reduces Decision Uncertainty

The case materials prove that, AI-led individualized content can, through two channels, greatly lower users’ uncertain degree in product-matching decision making.

In the conventional user operation flow of general AR try-on, users must browse and even test dozens or even hundreds of color numbers one by one. This procedure places a very large weight on cognitive resources, because users need to memorize which color tones, they have already tested and carry out implicit comparisons. In other words, users do not only evaluate products but also undertake the working memory load of handling the choice set. Cognitive load theory has promulgated the root of this difficult situation: the human working memory capacity is extremely limited, and when the scale of the choice set exceeds the capacity of cognitive processing, both the decision quality and the decision speed will decrease [7]. Just this difficult situation therefore leads to “too many choices” and the exhaustion of making decisions. The artificial intelligence propelled individualized content can effectively alleviate this problem. The module that does personalization based on skin tone directly decreases the size of the choice set from dozens of color shades to five to eight highly related shades, therefore reducing inner cognitive load by one magnitude order. One user, a 21-year-old person who has nice pale skin, said: “In the past, I needed to click on every lipstick one by one. Through ten attempts, my patience was finally exhausted by me. At present the system tells me “Reds with cool tone that fit you” directly, therefore I just test these three and thus I have finished my hesitation. Another person who has mixed-type skin gave comment:

“This foundation color matching is the thing that saves life. I in the past would order two to three color shades and send back at the minimum one. At present, through AR together with skin analysis that tells me my accurate color number, I just directly place the order. This result accords with the study of Lee and Benbasat, therefore they discovered that higher accuracy of recommendation system is connected with lower perceived uncertainty of decision making [4].

4.2 The Transformation Mechanism from Reduced Decision Uncertainty to Impulse Purchase Intention

The case materials indicate that the decrease of decision uncertainty does not directly bring about the occurrence of impulse buying. On the contrary, it sets free cognitive resources, lets emotional factors hold a leading position, and therefore thus indirectly helps the occurrence of impulse purchase. This point therefore indicates that the influence of individualized content upon impulsive purchase intention takes place with lowered uncertainty as a precondition.

This kind of phenomenon may be given explanation by the cognitive-affective system theory [14]. By this theory, the behavior that people have is produced by the mutual action between cognitive evaluation and the arousal of emotion. When decision uncertain situation is high, the "cold" cognition system holds a dominant position, it carries out unceasing information collection, contrast, and risk evaluation. This cognizes procedure by itself restrains the production of impulses, hence because impulse needs fast decision making, hence cognitive evaluation requires postponed judgment. This deduction accords with Kim and Lennon's results in the situation of online clothes buying, where the lessening of uncertainty about size and fit hence promoted impulsive buying through the reduction of cognitive effort and the increase of positive feeling [12].

4.3 The Moderating Effect of Personalization Degree on the Above Relationship: The Inverted U Shape Pattern

The degree of individual customization is not monotonically advantageous but rather displays an inverted U-shaped connection with impulse purchase intention, hence moderate customization produces the highest impulse conversion rate, hence both not enough and overmuch customization restrain impulse purchase. The A/B test outcome publicized by Sephora has compared three situations: low degree of individualization (only skin color filtration, showing more than 15 color numbers), medium degree of individualization (skin color filtration plus behavior-based ordering, showing five to eight color numbers), and high degree of individualization (only showing one or two most matching color numbers, with all other choices concealed). The experiment outcome indicated that the medium personalization situation had better performance than the rest two situations on both conversion rate and user satisfaction marks. Although the high personalization situation obtained the highest click-through ratio on the first-screen recommended product shades, the overall add-to-cart ratio was lower than that in the moderate situation—because users gave up the visit after they got bored or felt they were controlled.

McAlister and Pessemier in 1982 have put forward that when consumers carry out hedonic consumption, they possess an inborn demand for new things [15]. Repeated eating and drinking of same product kinds brings decreasing marginal utility, therefore making consumers actively go look for distinct products or experiences for keeping an optimum level of stimulation. When personalized recommendation systems become excessively narrow, they effectively deprive users of chances to fulfill their demands for pursuing diversity, hence leading to weariness and decreased participation. It is worth pointing out that, Sephora for a short time took away the "view all products" entry in one edition of high personalization, hence it caused a decrease in conversion rates; When the entry had been brought back, conversion rates very quickly got well again. This tiny point clearly shows that users require personalization to be a helping tool, not to be a replacement for their own personal decisions.

5 Suggestions

According to the three-dimensional analysis that surrounds the final research question which is put forward above, this section provides three concrete strategy suggestions to beauty brands and AR technology providers.

Carry out the construction of a dynamic graph which fuses skin color and behavior for recommendation. When design AI-driven individual suggestion systems, enterprises ought to give up the behavior of regarding personalization as one single dimension and therefore adopt a two-layer structural framework. The bottom layer ought to build hard filtering rules according to users' objective body features—skin tone depth, skin tone undertone, and skin sort—to guarantee all the recommended products have physical compatibility with the user. This layer has the function of eliminating the main source of product-matching uncertainty. The uppermost layer needs to construct a time-decay model that is based on historical behaviors, it assigns higher weight values to recent try-on behaviors (stay time, repeated try-ons, adding to cart), and lower weight values to actions that happened earlier. The recommendation system parameters, hence, need the continuous optimization by use of reinforcement learning methods, hence the system dynamically carries out feature adjustment on the basis of feedback signals, for example, whether users click, skip, or finally buy the recommended goods. The interview materials indicate that carrying out an update for the recommendation model every two weeks can assist with keeping freshness, and will not let users feel that the model "is unable to catch up" with their changing preferences.

Carry out the 80/20 personalization ratio principle in order to avoid the negative influences of the inverted U-shaped form. Business organizations should carry out control over the proportion of personalized recommendation works to be at a suitable level. In the interface design, an obvious "look through all goods" entrance should forever be given, letting users get out from the personal recommendation scope. In addition, one "surprise box" function can be added: after users finish three purchase behaviors which are led by personalized recommendation suggestions, the system can unlock a very new try-on recommendation that is beyond their ordinary preference

scope, thus utilizing the stimulating feeling from uncertainty to strengthen users' long-term use motivation.

Arrange instant emotional stimulations at moments with low uncertainty. The system ought to utilize real-time behavior indexes—for example, a user staying on a personalized recommended product for over five seconds, enlarging to examine particulars, or repeatedly trying the same color—to conclude that the user's uncertainty regarding this product has decreased to a relatively low degree. When this signal has appeared, therefore, the system ought to carry out the overlay of emotional arousal clue things on the interface. It is worth pointing out that, in the same conversation session, no more than two emotional appeals are permitted to be put forward, for the avoidance of psychological reactance, which would thus bring about the reduction of conversion [16].

6 Conclusion

6.1 Research Background

This paper carried out concentration on the core research question—“In what way does AI-pushed personalized content influence consumers' decision uncertainty and impulse purchase intention on mobile AR try-on?”—this research has carried out a deep-going analysis on the case of Sephora Virtual Artist; therefore, it has obtained the conclusions which follow. Firstly, artificial-intelligence-propelled individualized content greatly lowers users' product-matching decision uncertainty via two channels: reducing the selection scope and offering an impersonal reference. Second, the decrease of decision uncertainty can release cognitive resources, and this lets emotional excitation take the leading position in the decision-making process, thus it hence promotes the impulse purchase intention. Third, the degree of individuation displays an inverted U-shaped connection with impulsive purchase intention, with medium-level individuation (option group of about 5–8 articles, with independent browsing chances kept) generating the best result, while too much individuation negatively influences results through damaging user independence and pursuit of variety.

This study's theoretical contribution is that it uncovers the concrete mechanisms by which the personalized content driven by AI influences decision uncertainty and the impulse purchase intention in the AR try-on situation, it differentiates the different effects of personalization which based on skin tone and personalization which based on behavior, and therefore it ascertains the inverted U-shaped boundary condition of the degree of personalization. The practical contribution is that this paper puts forward three operable tactics: the dynamic recommendation drawing, the 80/20 proportion rule, and emotion stimulus at low-uncertainty time points.

The present investigation possesses several restrictive aspects. That the conclusions obtained from one single beauty case can be popularized to other product categories needs further verification work. The interview sample that this paper used mainly was composed of young women, it has no diversity. The factors which are about privacy concern have not been examined by us. In the future, research may be expanded to AR

try-on categories such as clothes and home furniture, by using mixed research methods with bigger samples to further test the robustness of the obtained results.

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