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Application of a Skin Prediction Algorithm for Personalized Skincare Services with Clinical Outcomes

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1. Introduction

Skin health is determined by a complex interplay of genetic, lifestyle, and environmental factors. While intrinsic aging mechanisms—driven by genetic and chronological processes—lead to progressive degradation of dermal structure and function, extrinsic stressors such as UV radiation, pollution, nutrition, and sleep patterns can significantly accelerate visible skin aging [1–5].

The exposome, a term introduced by Wild [6] and expanded in dermatology by Krutmann [7], encompasses all environmental exposures over a lifetime. Within this framework, factors like UV exposure, particulate matter, temperature changes, and behavioral choices collectively impact skin aging, inflammation, pigmentation, and barrier function. Mounting evidence underscores that lifestyle and environmental influences contribute more substantially to skin phenotypes than genetics alone [3,4,8].

At the same time, personalization has emerged as a dominant trend in the global skincare market. According to a 2023 international beauty industry survey, over 70% of consumers reported a strong preference for skincare solutions tailored to their individual skin conditions, lifestyles, and goals [4]. Increasingly, consumers expect more than just product customization; they seek expert-guided regimens that reflect their unique biological and environmental contexts. This includes optimizing product combinations, application routines, and behavioral strategies that align with their needs. Such evolving expectations have fueled the development of AI-based diagnostic tools, skin prediction algorithms, and hyper-personalized programs that integrate genetic, lifestyle, and environmental insights [3,4,9].

This convergence of stressors and consumer demands has led to a paradigm shift: from one-size-fits-all skincare to scientifically grounded, data-driven personalization. Our prior work, presented at the 2022 IFSCC Congress, introduced an AI-driven skin prediction algorithm that integrated genomic, environmental, and lifestyle data to forecast future skin vulnerabilities [9]. In that study, lifestyle and exposome-related variables accounted for ~75% of skin phenotype variability, emphasizing the impact of modifiable behaviors.

This study extends those findings by evaluating the clinical efficacy of prediction-guided, personalized skincare services in a real-world setting. We implemented a comprehensive diagnostic model incorporating (1) genetic markers for aging and barrier function, (2) skin phenotyping via clinical devices, and (3) lifestyle surveys. Using machine learning, individualized care plans were developed—encompassing product recommendations, usage routines, and behavioral interventions. We assessed changes in skin condition over eight weeks and evaluated sustained transformation in long-term participants.

2. Materials and Methods

2.1. Participants

The study recruited 38 Korean participants (30 females, 8 males) aged 20–40 years. All participants provided written informed consent and had no active dermatologic conditions or procedures within six months prior to the study. In addition to the main cohort, three additional participants who had previously undergone personalized skincare programs at City Lab were included for long-term case analysis. These participants (all female, aged 30–37) had revisited the lab more than three times over the course of 10–12 months and maintained a consistent skincare regimen guided by the same protocol.

2.2. Study Design

Participants underwent skin assessments and consultations at three time points: baseline (Week 0), Week 4, and Week 8. Based on the results of predictive modeling and diagnostics, each participant received a personalized skincare routine including product recommendations, application order, and lifestyle guidance. Routine adherence and subjective feedback were assessed through interviews and follow-ups.

2.3. Skin Diagnostics and Measurements

The following parameters were measured:
Wrinkles, Pores, Redness, Pigmentation, Porphyrins, Hydration, and Oil: Measured by MarkVu Sensor at the forehead and cheeks.
Elasticity: Measured using Cutometer MPA580 (Courage + Khazaka) at the cheeks and periorbital region.
TEWL (Transepidermal Water Loss): Measured with a Vapometer (Delfin Technologies) at the cheek area.
All skin parameters were converted into percentile scores standardized by age and gender using the City Lab database.

2.4. Genotyping and Genetic Data Processing

Buccal swab samples were collected and DNA was extracted and purified by LabGenomics (Seongnam, Korea). Instead of using genome-wide arrays, targeted exome sequencing was performed focusing on 69 DTC-permitted items approved by the Korean Ministry of Food and Drug Safety, encompassing approximately 200 genetic markers. Markers related to skin phenotypes—aging, pigmentation, moisture retention, and sensitivity—were extracted for analysis. Quality control was conducted by LabGenomics in accordance with regulatory guidelines.

2.5. Genetic, Phenotypic, and Lifestyle Data Integration

Three layers of data were integrated for each participant:
1) Genetic Markers: Including those associated with aging susceptibility, pigmentation, moisture barrier function, and sensitivity.

2) Phenotypic Assessments: Objective skin measurements from clinical-grade devices.
3) Lifestyle Surveys: Covering sun exposure, diet, sleep quality, stress, smoking, and skincare practices.
This multimodal approach enabled a holistic assessment of intrinsic and extrinsic factors affecting skin health.

2.6. Predictive Modeling and Machine Learning

To forecast future skin conditions, a machine learning model was developed with the following steps:
1) Feature Selection: Key genetic, lifestyle, and phenotypic parameters were selected to prevent overfitting.
2) Model Training: Gradient boosting algorithms (CatBoost, XGBoost) were used to model phenotype-specific predictions.
3) Class Imbalance Handling: When skin condition classes were unevenly distributed (e.g., worst to best), SMOTE (Synthetic Minority Over-sampling Technique) was applied to enhance prediction accuracy.

2.7. Diagnostic and Personalization Protocol

A multi-step protocol was applied to develop tailored skincare interventions:

1) Skin Type Classification (SOLUTION TYPE NO.):

To deliver tailored skincare solutions, participants were classified into 19 skin types (SOLUTION TYPE NO.) based on an algorithmic integration of instrument-based measurements and structured lifestyle questionnaires. This classification system reflects not only physiological skin characteristics such as moisture balance, oil secretion, and barrier integrity, but also subjective skin concerns such as dullness, sensitivity, and acne tendency.
Each type was defined by a combination of base skin type (dry, oily, combination, normal, or problem-prone) and predominant skin concerns.
The classification structure was as follows:

- Types 1–4: Dry skin (low hydration and oil), subtyped by aging, pigmentation, mixed, or no specific complaints.
- Types 5–8: Oily skin (high sebum, low barrier stability), with similar subdivisions.
- Types 9–12: Normal skin (balanced moisture/oil), differentiated by concern.
- Types 13–16: Combination skin (dehydrated-oily type), characterized by low moisture and excess sebum (commonly oily T-zone with dry U-zone).
- Types 17–19: Problem-prone skin, reflecting sensitivity, acne, or overlapping conditions.

This classification provided a framework for selecting customized skincare strategies based on the individual's skin condition and concern profile.

2) Personalized Product and Routine Mapping:

For each skin type, customized skincare routines were generated using a standardized mapping logic developed in collaboration with formulation scientists and dermatology experts. Recommendations included cleansers, toners, essences, serums, moisturizers, sunscreens, and exfoliants, with functional emphasis based on skin needs - e.g., barrier-supportive products for dry/sensitive skin or exfoliants for oily/acne-prone types.

3) Prediction-Based Consultation:

A predictive consultation model was employed to visualize future skin trajectories and support behavior change. The skin prediction algorithm integrated four layers of data: age, genetic markers, instrument-based skin phenotype measurements, and lifestyle survey responses. For each participant, the algorithm forecasted five key skin attributes—hydration, oil balance, elasticity, pigmentation risk, and sensitivity.

In addition, personalized prevention strategies were delivered based on inherent genetic risk. For individuals with higher predicted susceptibility to pigmentation, barrier dysfunction, or sensitivity—derived from their genotypic profile—anticipatory care routines were recommended. These included both product-based approaches and daily habit adjustments to manage vulnerability before symptoms appeared.

3. Results

3.1. Participant Characteristics Reveal Diverse Skin Concerns and Personalization Needs

A total of 38 participants (30 females and 8 males) aged between 20–40 years were included in the study. The majority were in their 30s (50%), followed by those in their 20s (27.5%) and 40s (22.5%). The most frequently reported skin concerns included dry skin (60%), visible pores (57.5%), loss of elasticity (57.5%), wrinkles (50%), hyperpigmentation (40%), dullness (37.5%), acne-prone skin (35%), sensitive skin (27.5%), redness (25%), rough skin texture (18.4%), oily skin (15.8%), and post-acne scars (13.2%) (Figure 1).

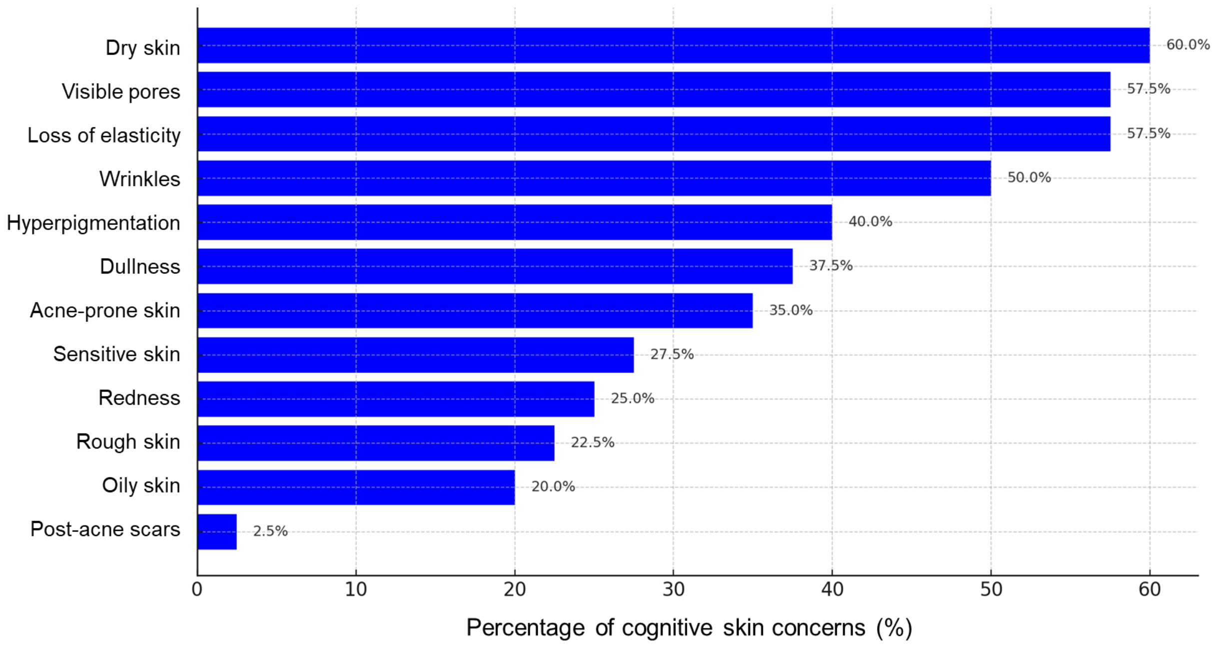

Figure 1. Percentage of cognitive skin concerns (%). Bar chart illustrating the percentage of participants reporting specific skin concerns, including dry skin, visible pores, loss of elasticity, wrinkles, hyperpigmentation, dullness, acne-prone skin, sensitive skin, redness, rough skin, oily skin, and post-acne scars. These results highlight the need for multifactorial personalized interventions based on both intrinsic and extrinsic skin profiles.

Distinct patterns were observed across age groups. Participants in their 20s primarily reported acne-related concerns, visible pores, and uneven tone, driven by preventive motivations. Those in their 30s expressed concerns about elasticity, dryness, and early wrinkles, indicating an emerging need for anti-aging care. Participants in their 40s were particularly focused on visible signs of aging, including pigmentation and wrinkles, and strongly desired tangible improvement. Across all ages, psychological uncertainty regarding routine effectiveness was prevalent, underscoring the need for expert-guided, data-driven personalization.

3.2. Personalized Skincare Program Demonstrates Clinically Meaningful Improvements Over 8 Weeks

Participants showed consistent and clinically meaningful improvements in overall skin health following eight weeks of personalized skincare intervention. Table 1 and Figure 2 summarize the average percentile changes across major skin parameters. The mean skin score improved by 13.1%, with the most prominent gains observed in elasticity (+42.5%), transepidermal water loss (+37.1%), redness (+18.2%), porphyrin levels (−13.5%), and U-zone hydration (+10.3%).

Table 1. Skin Parameter Improvements Over 8 Weeks (n = 38)

Parameter	Week 0	Week 4	Week 8	Change (%)	p-value
Pores	74.1	74.2	75.9	+2.4% ↑	0.36
Wrinkles	57.0	57.3	57.6	+1.1% ↑	0.46
Pigmentation	47.1	47.3	48.6	+3.2% ↑	0.17
Redness	36.2	37.2	42.8	+18.2% ↑	0.18
Porphyrin	71.1	77.5	80.7	+13.5%▲	0.04
Elasticity	41.8	45.2	59.6	+42.5%▲	5e-05
TEWL (Barrier)	23.2	23.7	31.8	+37.1%*▲	0.01
T-zone Hydration	27.3	27.9	28.8	+5.5% ↑	0.05
U-zone Hydration	24.1	25.9	26.6	+10.3%▲	0.0003

Mean percentile scores for key skin health indicators measured at baseline (Week 0), midpoint (Week 4), and endpoint (Week 8). Improvements reflect clinically meaningful changes in elasticity, barrier function, redness, and hydration following the personalized skincare program. *TEWL values represent improvement in barrier function (higher percentile = lower actual TEWL). ▲ $p < 0.05$ (statistically significant); ↑ $p \geq 0.5$ (non-significant change)

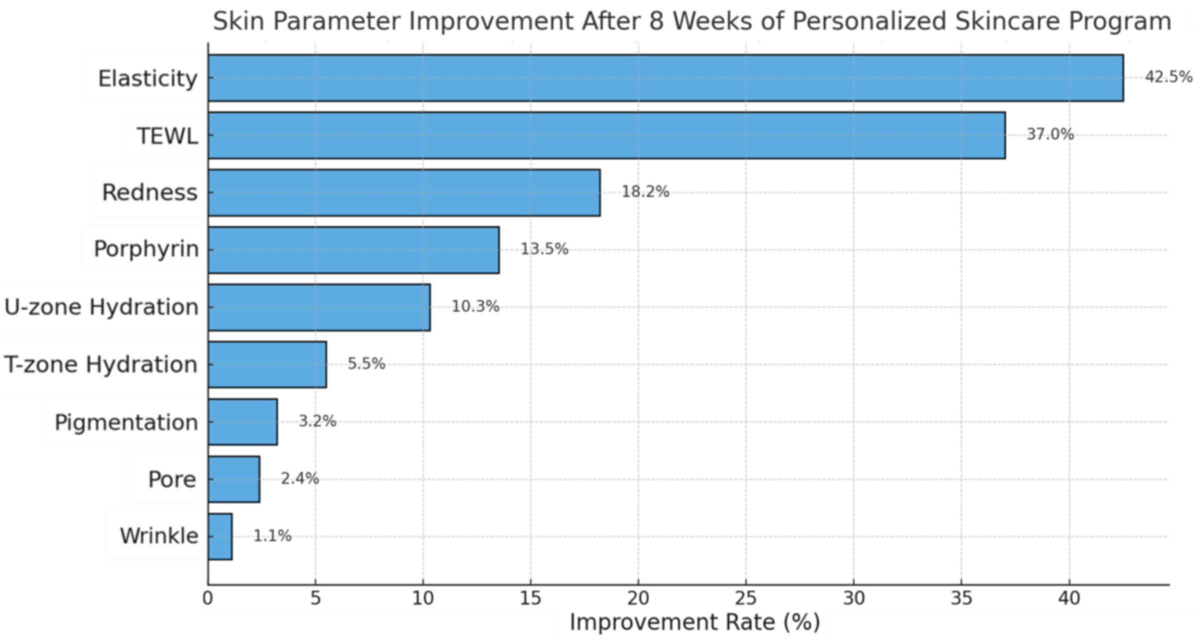

Figure 2. Percentile-Based Changes in Skin Parameters Over 8 Weeks

Graphical representation of the mean trajectory of skin parameter improvements across eight weeks. Notable gains were observed in elasticity, TEWL (barrier function), and redness, highlighting the efficacy of personalized interventions.
A closer domain-specific analysis revealed several distinct response patterns:

- Elasticity exhibited the most substantial improvement, particularly among participants who adopted anti-aging ingredients such as retinol, peptides, and PDRN. In some cases, enhanced elasticity was accompanied by reductions in pore size, suggesting synergy between dermal firming and surface refinement strategies.
- TEWL, a marker of barrier integrity, improved significantly among participants using barrier-repair-focused routines with ceramides, allantoin, and humectants. Improved barrier function was also linked to reduced sensitivity and inflammation.
- Redness decreased notably in sensitive skin types, especially when low-dose retinoids were combined with calming agents like centella asiatica extract, panthenol, and niacinamide.
- Porphyrin levels, reflecting sebaceous oxidation and acne-related bacterial activity, declined by 13.5%, particularly in users of antioxidant and exfoliant combinations (e.g., vitamin C, EGCG, AHA).
- U-zone hydration increased by 10.3%, contributing to improved comfort and resilience in areas prone to dryness.

In addition to mean improvements, a paired t-test was conducted to assess the statistical significance of these changes. Among the nine parameters, five demonstrated statistically significant improvement ($p < 0.05$):

- Elasticity ($p = 0.00005$)
- Porphyrins ($p = 0.04$)
- TEWL ($p = 0.01$)
- U-zone hydration ($p = 0.0003$)
- T-zone hydration ($p = 0.05$) showed marginal significance.

Pigmentation ($p = 0.1732$) and redness ($p = 0.1819$) showed moderate but non-significant improvement, while pores and wrinkles exhibited minimal statistical change.
These findings suggest a hierarchical skin response pattern in personalized skincare:

- In the early phase (within 8 weeks), the most responsive domains were hydration and barrier repair, reflecting the rapid effect of product adherence and basic lifestyle changes (e.g., consistent sunscreen use, improved sleep, balanced nutrition).
- Elasticity improvements appeared as a second-tier outcome, supported by a combination of dermo-cosmetic strategies and behavior-based compliance.
- Pigmentation and wrinkles, which are linked to longer biological turnover (e.g., melanogenesis, collagen remodeling), may require extended interventions to achieve statistically significant improvements. Nevertheless, the underlying enhancement in barrier health and inflammation control likely contributes to favorable conditions for long-term structural and tonal improvement.

Collectively, these results demonstrate that personalized skincare—grounded in skin diagnostics, routine optimization, and behavior-based coaching—can induce clinically meaningful and statistically supported improvements in key skin health domains within a relatively short time. The program’s success in improving foundational skin resilience also positions it as a viable preventive approach for longer-term skin aging and pigmentation control, which are further explored in the subsequent sections.

3.3. Sustained Improvements in Skin Parameters Through Long-Term Adherence to Personalized Routines

To evaluate the durability of intervention effects, three participants were monitored over a 10–12 months period following their enrollment in the personalized skincare program. These individuals revisited City Lab multiple times and demonstrated consistent adherence to the prescribed skincare routines and lifestyle recommendations. Detailed case profiles are summarized in Table 2.

Table 2. Summary of Long-Term Skin Improvements and Type Transitions in Three Participants (10–12 months adherence to personalized skincare and lifestyle guidance)

Category	Case 1 (Dry + Acne)	Case 2 (Oily + Pigmentation)	Case 3 (Sensitive + Dullness)
Skin Concerns	Elasticity loss, pores, acne, flakiness	Dullness, melasma, excess sebum	Redness, pigmentation, dryness, wrinkles
Diagnostic Summary	Barrier weakness, low elasticity, TEWL↑	Pigmentation & oil imbalance	Barrier damage, redness, pigmentation
Core Challenges	TEWL↑, Pore↑, Elasticity↓	Melanin↑, Sebum↑	TEWL↑, Redness↑
Strategy	Barrier repair + anti-inflammatories + collagen boost	Pigmentation care + oil control + antioxidants	Redness reduction + hydration + gentle actives
Key Actives	PDRN, Madecassoside, Collagen, Ceramides	Vitamin C, Niacinamide, EGCG, Retinol	Ceramides, PDRN, Panthenol, Antioxidants
Routine Highlights	AHA/BHA → PDRN → Repair Cream → Mineral Sunscreen	Niacinamide → VitC/GSH or Retinol (night) → Moisturizer	Mild Cleanser → Niacinamide + PDRN → Hydration Cream
Lifestyle Guidance	Early sleep, sugar control, omega-3	Sleep in darkness, reduce glycemic foods	Avoid spicy food, sunscreen adherence
Score Improvements	TEWL +42.8%, Pores +31.9%, Redness +27.7%	Porphyrins -56%, Pores +29%, Redness +28%	TEWL +59%, Pigmentation +30%, Wrinkles +20%
Skin Type Transition	Type 16 (Combination) → Type 12 (Normal)	Type 18 (Oily/Acne) → Type 10 (Normal/Pigment)	Type 17 (Sensitive) → Type 2 (Dry/Pigment)

Each case represented a distinct phenotype and concern profile—ranging from dry acne-prone (Case 1), oily pigmented (Case 2), to sensitive dull skin (Case 3). All participants demonstrated meaningful improvements in clinical metrics such as TEWL, redness, pores, and pigmentation, alongside self-reported enhancements in skin texture, comfort, and makeup adherence.

Importantly, all three cases experienced a shift in skin type classification, indicating fundamental physiological recovery. For example, Case 1 transitioned from a combination to normal type (Type 16 → 12), suggesting normalized sebum regulation and barrier function. Case 2 moved from oily-acne-prone (Type 18) to normal-pigment prone (Type 10), reflecting suppressed sebaceous activity and reduced pigmentation load. Case 3, initially classified as sensitive (Type

17), stabilized into a drier but more controlled Type 2 profile, with lower redness and improved resilience.

These findings reinforce the cumulative and transformative potential of algorithm-informed skincare when sustained over time with behaviorally anchored guidance. Not only were quantitative improvements maintained, but the categorical shift in phenotype supports the idea that skin condition is a dynamic continuum—modifiable through sustained, personalized care.

This longitudinal evidence underscores a key message: when precision skincare is matched with consistent behavioral reinforcement, skin health is not only recoverable—but structurally reconfigurable.

4. Discussion

This study provides clinical evidence that personalized skincare—developed through integrated diagnostics combining predictive modeling, lifestyle analysis, and biometric assessment—can yield both statistically and clinically meaningful improvements in skin condition over a short period. Notably, elasticity (+42.5%), transepidermal water loss (TEWL; +37.1%), and redness (−18.2%) emerged as the most responsive parameters during the 8-week intervention, demonstrating the early efficacy of addressing both intrinsic and extrinsic skin vulnerabilities.

These improvements extend beyond product efficacy, highlighting the value of multi-layered personalization grounded in lifestyle-based diagnostics. Participants received tailored interventions not only based on their phenotypic profiles but also on modifiable lifestyle factors such as sleep, UV exposure, and nutrition—factors previously shown to exert a greater influence on skin aging than genetics alone [1,4,6]. This is further substantiated by our prior exposome modeling study, which revealed that approximately 75% of skin phenotype variability among Korean women could be explained by lifestyle and environmental influences [9].

A key driver of engagement in this program was the use of AI-based skin prediction visualizations during 1:1 consultations. By illustrating potential skin trajectories under different behavioral scenarios, these tools increased participants' awareness and perceived control, thereby enhancing adherence. This is consistent with established behavioral science principles—including self-efficacy theory and motivational interviewing—which emphasize the motivational power of visualizing outcome change.

The 10–12-month follow-up of three high-adherence participants demonstrated that algorithm-informed skincare can produce sustained benefits, including continued improvements in clinical metrics and categorical skin type conversion (e.g., from oily-acne-prone to stable dry/pigment-prone profiles). These findings underscore that skin condition is not static, but rather a dynamic and modifiable continuum shaped by consistent, personalized care.

Moreover, participants with multifactorial or overlapping concerns—such as dryness with acne, or sensitivity with pigmentation—exhibited the most notable improvement. These outcomes emphasize the importance of combining concern-specific actives (e.g., PDRN, ceramides, antioxidants) with tailored lifestyle coaching. The synergistic benefits observed across hydration, pigmentation, sensitivity, and barrier function would likely not have been achieved through generalized regimens alone.

Taken together, this study supports the transition from conventional product-centric approaches to precision skincare frameworks that integrate diagnostics, prediction, consultation, and behavior change support. Such models reflect a growing global shift toward preventive, data-driven skincare for long-term health and longevity.

As summarized in Table 3, the three-phase structure of our program—anchored in lifestyle-based diagnostics, personalized care planning, and behaviorally guided adherence—provides a scalable model for sustainable, patient-centered skin health management.

Table 3. Summary of the Personalized Skincare Program Phases and Expected Benefits. A structured overview of the program's three-phase approach, highlighting its diagnostic foundation, personalized routine strategy, and adherence-enhancing mechanisms to support sustainable skin improvement.

Program Phase	Core Concept	Key Elements	Expected Benefit
Self-Assessment (Diagnosis)	Lifestyle-based Integrated Skin Diagnostics	Combined analysis of skin condition, lifestyle, and concern using AI prediction model	Enhanced awareness of current condition Early identification of potential issues
Routine Design (Strategy)	Concern-specific Personalized Care Planning	Customized regimens including targeted actives Coaching on sleep, diet, UV protection	Optimized treatment plan Increased perceived efficacy
Sustained Practice (Execution)	Motivation through Predictive Visualization	Visual forecast graphs to promote self-efficacy and encourage consistent routines	Long-term improvement Higher adherence and autonomous care behaviors

5. Conclusion

This study confirms that lifestyle-integrated diagnostic algorithms can effectively guide personalized skincare interventions that yield meaningful short-term improvements in elasticity, hydration, and barrier function. Over eight weeks, participants achieved clinically relevant changes, particularly in domains most responsive to behavioral modulation and targeted care. More significantly, long-term follow-up revealed that sustained adherence to prediction-informed routines can lead to categorical skin type shifts and continued improvement in skin resilience. These findings underscore the modifiability of skin health through tailored, behaviorally supported routines, particularly when informed by multidimensional diagnostics.

By combining AI-powered forecasting, expert consultation, and individualized habit coaching, this approach fosters routine adherence and enhances self-efficacy in managing one's skin health. This integrative framework offers a scalable model for the next generation of personalized skincare services and serves as a practical blueprint for preventive dermatology, skin longevity strategies, and wellness-based beauty innovation.

6. References

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