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PAPER

An Android-Based mHealth App for Color Vision Screening and Career Guidance: Design and Validation

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ABSTRACT

Color vision deficiency (CVD) affects learning outcomes, career opportunities, and daily life, but early screening in Vietnam remains limited. This study introduces an Android-based mobile health (mHealth) application for CVD screening, integrated with an artificial intelligence (AI) module for career guidance. The app was deployed with 527 high school students in Da Nang and validated against standard printed Ishihara plates. Results showed complete agreement with the traditional test, faster screening time, and positive feedback on ease of use and usefulness. The majority of students rated the CVD simulation and career guidance functions as valuable. This research contributes by (1) validating a CVD mHealth tool on a large student population in real educational settings, (2) integrating AI to link health screening with career orientation, and (3) demonstrating a cost-effective, scalable digital solution that supports both school health programs and personalized career counseling. The findings emphasize the role of engineering innovations in enhancing education and health support for students.

KEYWORDS

career guidance, Ishihara test, mobile health application, color vision screening, color vision deficiency (CVD)

1 INTRODUCTION

Color vision deficiency (CVD) is a visual impairment characterized by a reduced ability to accurately distinguish specific colors. It most commonly affects perception within the red–green spectrum (protan and deutan types), occurs less frequently in the blue–yellow spectrum (tritan), and in rare cases manifests as total color blindness, or achromatopsia [1], [2].

Epidemiological data from the 1958 British birth cohort revealed that approximately 6.7% of males exhibited congenital CVD when assessed at age 11 using the Ishihara color vision test [3]. The Ishihara test remains the most widely used tool for CVD screening in clinical and educational contexts [4]. While CVD does not result

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in complete vision loss, it may significantly hinder educational experiences, limit access to color-critical professions, and pose safety concerns in occupational settings where accurate color discrimination is essential [5].

Mobile health (mHealth) applications have recently emerged as effective tools for remote health screening, offering advantages such as accessibility, low cost, and user-friendliness, particularly among adolescents and students [6], [7]. Reviews have emphasized that mHealth solutions can significantly improve healthcare delivery and are increasingly relevant for large-scale adoption [8], [9]. In the field of vision health, digital adaptations of the Ishihara test have been developed and positively evaluated, ranging from simple mobile prototypes to advanced augmented reality (AR) systems. For example, an AR-based solution integrated with language models was demonstrated to support CVD users [10], underscoring the potential of digital tools to enhance accessibility. Mobile AI-based systems have also been applied to ophthalmology tasks, such as detecting pterygium from anterior segment images using convolutional neural networks [11].

However, most existing applications remain limited in scope. They have rarely been validated through large-scale field trials in real educational settings, and almost none integrate additional features to support students' long-term educational or career development. Addressing this gap, the present study designs, implements, and validates an Android-based mHealth application for CVD screening in Vietnamese high schools, while also integrating an artificial intelligence (AI)-driven module for career guidance. This dual approach seeks to ensure both technical accuracy and practical relevance for school-based health and education programs.

2 LITERATURE REVIEW

International epidemiological studies have shown that CVD is a congenital visual disorder with a significant prevalence, particularly among males. CVD affects approximately 8% of males and 0.5% of females in European and Asian populations [1]. Beyond Ishihara-based assessments, comparisons between mobile apps and conventional visual evaluation methods have reported reliability comparable to bucket and virtual systems [12]. In Vietnam, a survey by Yen [13] among high school students reported a prevalence of about 3.2%, with most cases remaining undetected or never subjected to specialized screening. This situation has potential implications for career orientation and students' ability to engage in activities requiring accurate color perception. Similarly, Duc [14] evaluated visual function in cadet students at four police academies in Hanoi and found that many exhibited undetected CVD despite passing standard vision tests, highlighting the need for more comprehensive pre-admission screening.

The Ishihara test, introduced in 1917, is widely recognized as the standard method for detecting red–green color vision deficiencies [15]. Although reliable in clinical practice and occupational screening, its printed version faces practical limitations, including dependence on standardized lighting, limited durability, and restricted scalability. To overcome these challenges, digital adaptations have been proposed. Digital adaptations have been proposed, and several commercial applications, such as Colorblind Check, Color Blind Test, and Color Vision Simulator, have been released for Android and iOS platforms [9]. However, most of these tools have not undergone rigorous validation against clinical standards or peer-reviewed evaluation.

Within the broader context of digital transformation, mHealth has emerged as a promising approach. mHealth is defined as the use of mobile devices and wireless technologies to support healthcare [7]. Recent reviews confirm that mHealth applications offer broad accessibility, low cost, and personalization, making them particularly suitable for young, technology-savvy populations [8], [9]. In addition, Abbas et al. [8] highlighted the growing significance of mHealth for large-scale healthcare delivery, while Haque and Rahman [9] emphasized its role in improving adolescent healthcare. In the field of vision health, Morita et al. [10] demonstrated an augmented reality solution combined with language models to support CVD users in real-world tasks, underscoring the potential of digital tools for accessibility.

In Vietnam, Yen [13] proposed an information technology–based model for school-based CVD surveys, integrating screening results into educational and career guidance systems. Nevertheless, there remains a lack of research focusing on developing a dedicated mobile application that not only meets clinical standards but is also validated through large-scale field trials in real educational settings. Furthermore, no prior studies have integrated screening outcomes with AI-based career guidance. This research gap underpins the present study, which aims to design and evaluate an Android-based mHealth application integrating the Ishihara test with career guidance features, providing a reliable, user-friendly, and context-appropriate tool for CVD screening in Vietnamese high schools.

3 MATERIALS AND METHODS

3.1 Artificial intelligence application development process

The development of the CVD application followed the Agile software development model, ensuring flexibility in adjusting functionalities and the user interface based on feedback from the target user group. The development process comprised several key stages: requirement identification and problem analysis, system architecture and interface design, programming and integration of algorithms for processing color vision screening data, internal testing, training of the analytical module using trial data, and finally, deployment of the beta version to a group of real users (see Figure 1).

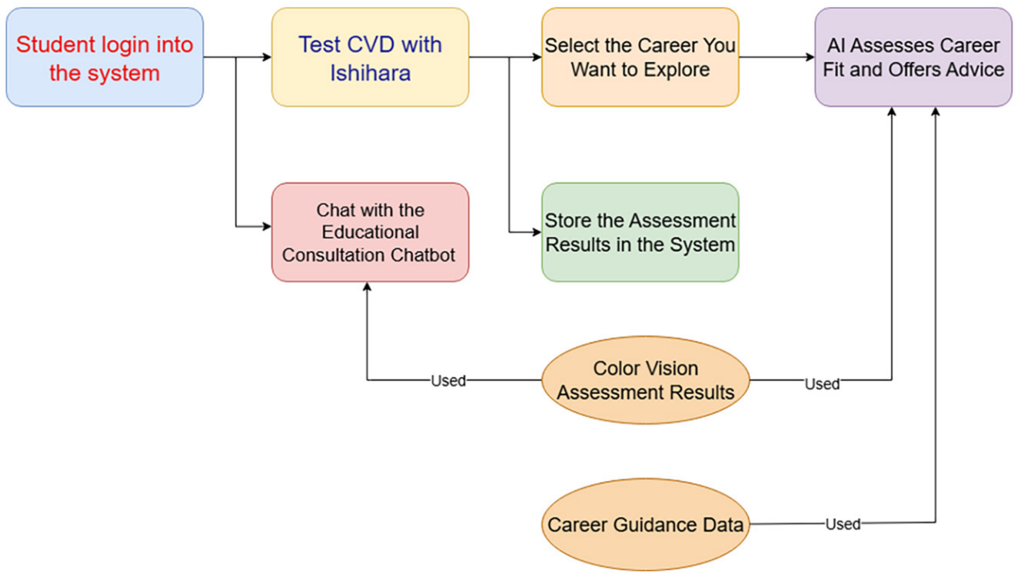

Fig. 1. Flowchart of the development process for the AI-based Android application for CVD screening

To enhance clarity and comprehension, the development process is illustrated in a flowchart that depicts the relationships between stages, from requirements gathering to application deployment and user feedback collection.

3.2 System design

The application was developed for the Android platform using Kotlin and the Android SDK and follows a three-layer architecture (see Figure 2). The user interface layer displays Ishihara test plates, collects responses, and presents results. The logic layer applies Ishihara scoring rules, processes inputs, and manages AI-driven recommendations. The data layer stores screening results and accesses the career guidance dataset.

The screening module uses 38 high-resolution Ishihara plates (38-plate edition), while the career-guidance module queries a curated dataset from national educational guidelines and occupational handbooks to map screening outcomes to recommended study fields and careers. The AI module leverages a large language model (LLM), a deep learning architecture trained for natural language understanding and prediction, combined with prompt-engineering techniques to generate career guidance recommendations aligned with the curated dataset.

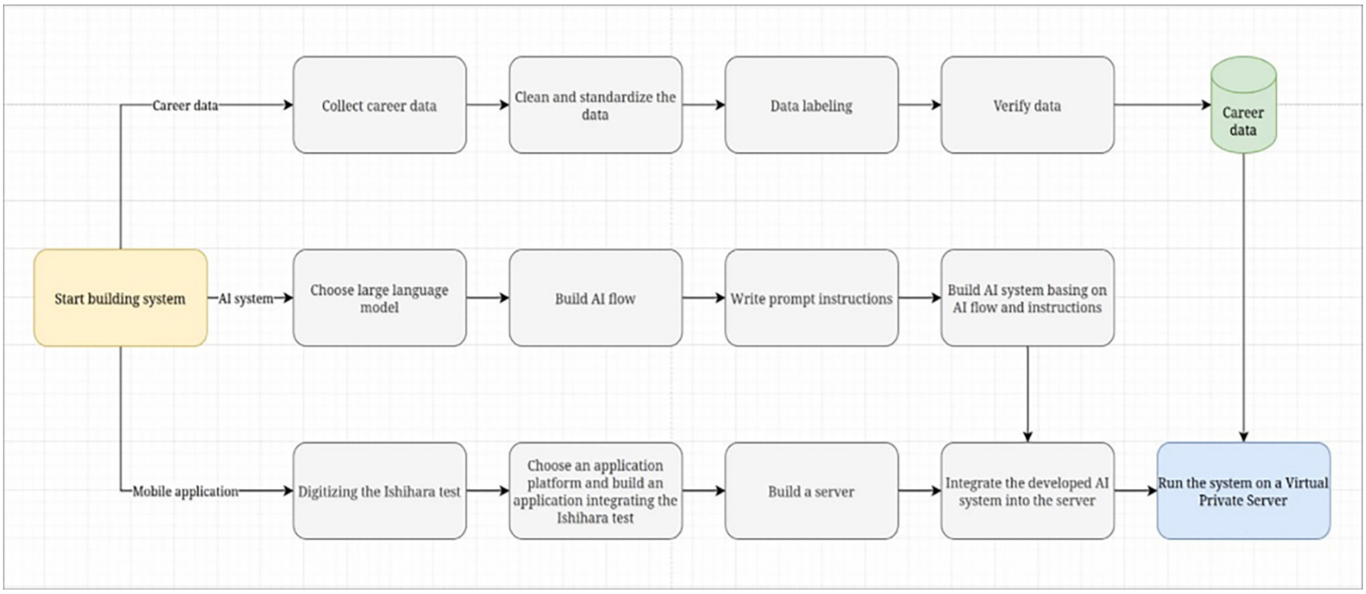

Fig. 2. Three-layer architecture (UI–Logic–Data) of the Android-based mHealth app, integrating 38 Ishihara plates and a career-guidance dataset for CVD screening and AI-driven recommendations

User interface of the Android-based mHealth application for color vision deficiency screening. The interface includes the home screen, Ishihara test display, result summary, CVD vision simulation, and AI-based career guidance recommendation screen.

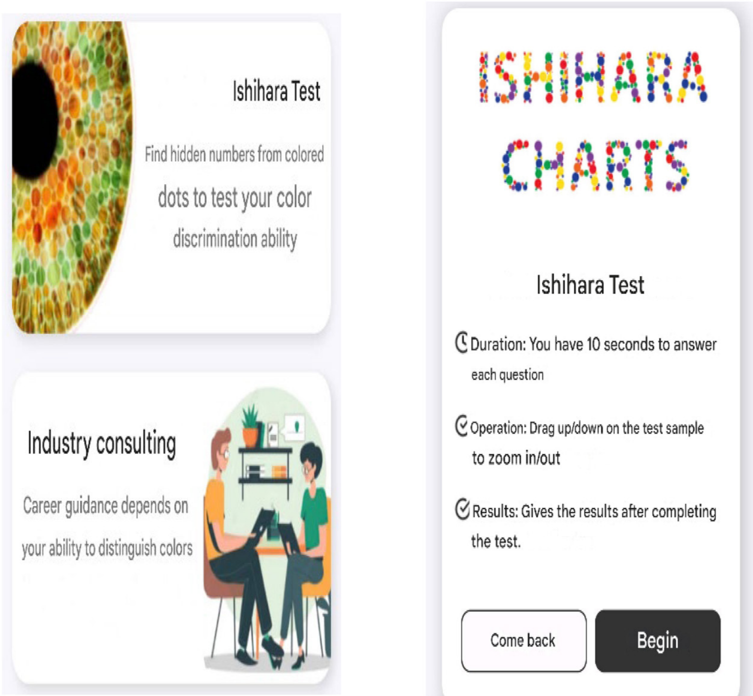

Fig. 3. User interface of the Android-based mHealth application for color vision deficiency screening

Figure 3 presents the primary interface of the color vision testing application designed by the research team. Each test plate is displayed for a fixed duration of about 10 seconds to promote fairness and reduce the likelihood of random guessing or extended contemplation that might influence accuracy. The application also allows users to zoom in and out on the test images, providing clearer visibility and better accessibility for students with different levels of visual acuity.

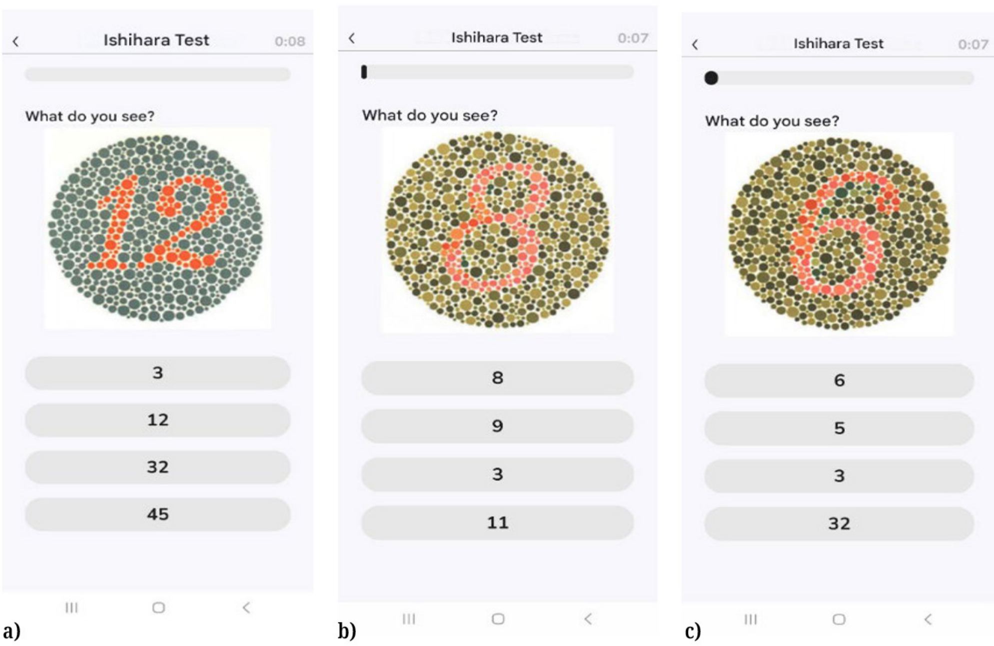

Fig. 4. Example screens of the Ishihara color vision test in the Android-based mHealth application

In Figure 4a, the numeral 12 is identifiable by both individuals with normal color vision and those affected by CVD. In Figure 4b, participants with normal vision typically recognize the number 8, whereas individuals with red-green deficiencies are more likely to report seeing the number 3. In Figure 4c, the numeral 6 is typically recognized by individuals with normal color vision, whereas those with red-green deficiency often read it as the number 5. The mobile application incorporates all 38 Ishihara plates, enabling students to conveniently perform self-screening for potential color-vision issues.

The system automatically records and analyzes results, enabling comparison with printed Ishihara test outcomes to assess diagnostic accuracy. Field trials in Da Nang high schools demonstrated high agreement rates and a reduction in testing time compared to traditional methods.

The software classifies CVD by type and severity (e.g., protanopia, deuteranopia, and complete color blindness), offering data to support tailored educational and career counseling.

Usability survey results showed that most students preferred the mobile version over the paper-based test, citing convenience and ease of use. Upon completing the screening, users can access the career guidance module via the "Industry Consulting" feature (see Figures 3 and 5), or proceed directly to it, where recommendations align with existing academic programs.

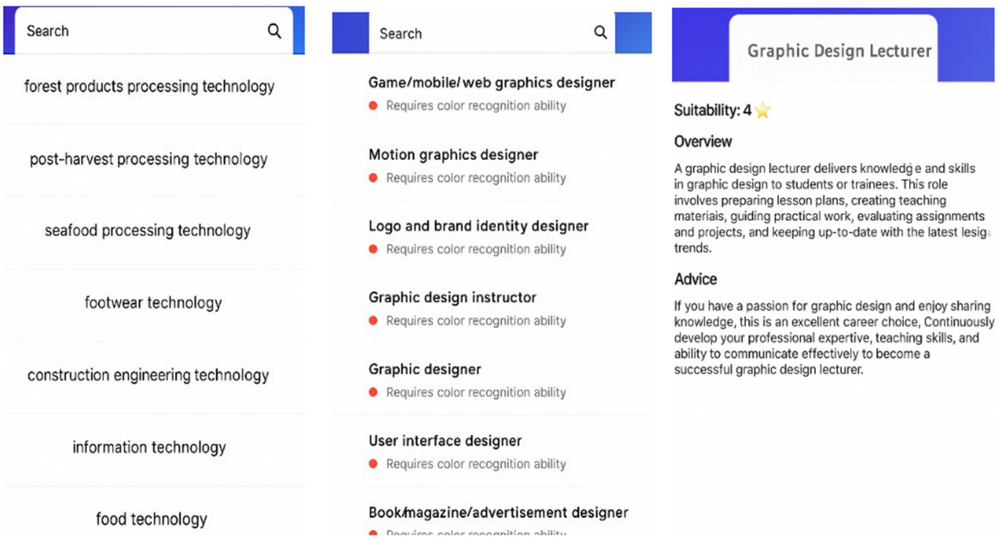

Fig. 5. Career guidance content interface screen for students

Figure 5 shows the interface of the career guidance module presented to students. The screen displays recommended fields of study and occupations generated by the AI module, based on mapping between screening outcomes and the curated dataset. This design ensures that students receive not only their CVD screening outcomes but also immediate, tailored career guidance. Such integration enhances the educational relevance of the application and demonstrates its novelty compared with previous digital CVD tools that focused solely on screening.

3.3 Field survey and data collection

Following the development of the trial version described in Section 3.2, a field survey was conducted to evaluate the system's functionality and usability in a real-world educational context. The survey involved 527 high school students from five schools in Da Nang City, Vietnam. All participants performed the Ishihara color vision screening using the developed application (refer to Table 1).

Seventeen students (3.2%) were flagged with potential color vision anomalies. These cases were retested using printed Ishihara plates under supervision, showing a 100% match with app-based results, thereby confirming the screening accuracy of the application.

Table 1. Demographic characteristics of respondents

High Schools		Female	Male	CVD	Total
Code	1	44	61	4	105
	2	30	55	2	85
	3	45	73	4	118
	4	42	60	4	102
	5	48	69	3	117
Total		209	318	17	527

In parallel, participants completed a structured questionnaire rated on a five-point Likert scale (1 = lowest, 5 = highest). The instrument captured feedback across two components:

- AI-based career guidance system: awareness (AW), trust (TR), perceived benefits (PE), system concerns (BR), user expectations (EX), and readiness to adopt (RD).
- Color vision screening app: satisfaction (OS), perceived accuracy (QA), convenience (TC), user experience (EE), and comparison with traditional methods (CT).

Responses were analyzed using SPSS 27.0. Descriptive statistics and Cronbach's alpha were used to evaluate scale consistency and user attitudes toward both systems in an educational context. To validate the career guidance recommendations, outputs from the AI module were reviewed by educational counselors and cross-checked against national occupational handbooks and MOET guidelines. In addition, participants rated the perceived relevance and usefulness of the suggested study fields and careers on the Likert scale. This dual validation ensured that recommendations were both technically consistent with authoritative resources and practically meaningful for students.

4 RESULTS

4.1 Color vision screening outcomes

The field implementation of the developed Android-based color vision screening application involved 527 high school students from five schools in Da Nang City.

The application identified 17 students (refer to Table 2) with indications of color vision deficiency: six suspected protan cases, eight suspected deutan cases, two cases of isolated red color deficiency, and one suspected case of total color blindness. All identified cases were subsequently re-examined using the standard printed Ishihara plates under the supervision of school health personnel. The comparison between the two methods showed complete agreement with the printed Ishihara plates in this sample.

Table 2. Frequency of types of color blindness of students

Types of Color Blindness	Male		Female	
	Quantity	%	Quantity	%
Total number of students	318	100	209	100
Red–green color vision deficiency	6	1.95 ± 1.55	0	0.00 ± 0.00
Protanopia	7	2.27 ± 1.67	0	0.00 ± 0.00
Deuteranopia	3	0.97 ± 0.56	0	0.00 ± 0.00
Complete color blindness	1	0.32 ± 0.63	0	0.00 ± 0.00
Overall number of students with CVD	17	5.52 ± 1.30	0	0.00 ± 0.00

The screening was conducted on 527 high school students from five schools in Da Nang City, including 318 males (60.3%) and 209 females (39.7%). Using the developed Android-based application, 17 students (3.2% of the total sample) were identified as having potential CVD. Among male students, the most frequent type of CVD was green color vision deficiency (2.27 ± 1.67%), followed by red–green color vision deficiency (1.95 ± 1.55%), red color vision deficiency (0.97 ± 0.56%), and complete color blindness (0.32 ± 0.63%). No female students in the sample were found to have color vision deficiency.

Table 3. Comparison of color vision screening results between the mobile application and the standard printed Ishihara test

Classification of Color Vision Deficiency	Identified by Application (n)	Identified by Printed Ishihara (n)	Match (%)
Red–green color vision deficiency	6	6	100
Protanopia	7	7	100
Deuteranopia	3	3	100
Complete color blindness	1	1	100
Total	**17**	**17**	**100**

All 17 students identified by the application were retested using standard printed Ishihara plates under professional supervision. The results fully matched across all classification types, confirming 100% consistency and validating the app's accuracy for preliminary CVD screening (refer to Table 3). These findings confirm that the developed application achieved perfect consistency with the clinical standard, validating its reliability for preliminary CVD screening in school settings.

4.2 User feedback on the application and AI-based guidance system

Reliability analysis. User feedback was analyzed in two key areas: (1) perceptions of the AI-based career guidance system and (2) evaluation of the mobile color vision screening application. Responses were rated on a five-point Likert scale (1 = lowest agreement, 5 = highest agreement). Descriptive statistics and internal consistency analysis using Cronbach's alpha were conducted to assess scale reliability.

For the AI-based career guidance system, 18 items across six dimensions—awareness (AW), trust (TR), perceived effectiveness (PE), brand reputation (BR), user experience (EX), and recommendation disposition (RD)—yielded a Cronbach's alpha of 0.857 (refer to Table 4), indicating high internal consistency. All item-total correlations exceeded the 0.30 threshold, and deleting individual items resulted in negligible changes (α = 0.846–0.853), suggesting all items contributed meaningfully to the construct.

Table 4. Reliability for AI-based career guidance system

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha-Based on Standardized Items	No. of Items
0.857	0.857	18

For the color vision screening app, 15 items were grouped into five dimensions: satisfaction (OS), accuracy (QA), convenience (TC), experience (EE), and comparison with traditional methods (CT). The overall alpha was 0.839 (refer to Table 5), with item-total correlations from 0.411 to 0.553. Item deletion yielded minimal variation (α = 0.823–0.832), supporting the reliability of the scale.

Table 5. Reliability for mobile color vision screening app

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha-Based on Standardized Items	No. of Items
0.839	0.841	15

These results confirm both instruments are statistically robust and appropriate for evaluating user satisfaction, trust, and usability in the developed systems. This indicates that both instruments were statistically robust and suitable for evaluating user trust and satisfaction with the systems.

Exploratory factor analysis. Exploratory factor analysis (EFA) was conducted to assess the construct validity of both evaluation scales, using principal component analysis with Varimax rotation. The dataset suitability was confirmed by the Kaiser–Meyer–Olkin (KMO) measures and Bartlett's Tests of Sphericity, all exceeding recommended thresholds (refer to Tables 6 and 7).

Table 6. KMO and Bartlett's test for AI-based career guidance system

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.826
Bartlett's Test of Sphericity	Approx. Chi-Square	3601.153
	df	153
	Sig.	0.000

The EFA extracted six factors aligned with the theoretical structure: EX, RD, BR, TR, AW, and PE. All items loaded strongly (> 0.70) on their respective components without cross-loading, confirming convergent and discriminant validity.

Detailed factor loadings of the AI-based career guidance system are reported in Appendix A (refer to Table A1). The extracted factor structures aligned with the theoretical model, supporting the construct validity of the scales. Similarly, the construct validity of the mobile CVD screening application scale was verified.

Table 7. KMO and Bartlett's test for CVD screening app evaluation

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.804
Bartlett's Test of Sphericity	Approx. Chi-Square	3105.972
	df	105
	Sig.	0.000

Five factors were extracted, reflecting the structure of CT, EE, OS, QA, and TC. All items loaded above 0.70 on their intended components, supporting scale reliability and factorial validity. Detailed factor loadings of the CVD screening application are reported in Appendix A (refer to Table A2).

This result confirms that the scale items are well-structured, with each set of items measuring a distinct construct, and can therefore be used reliably in subsequent analyses, including descriptive statistics and group comparisons.

Descriptive statistics. The dataset suitability was confirmed by the Kaiser–Meyer–Olkin (KMO) measures and Bartlett's Tests of Sphericity, all exceeding recommended thresholds (Tables 6 and 7). Descriptive statistics for the AI-based career guidance system are summarized in Figure 6, while full item-level results are provided in Appendix A (refer to Table A3).

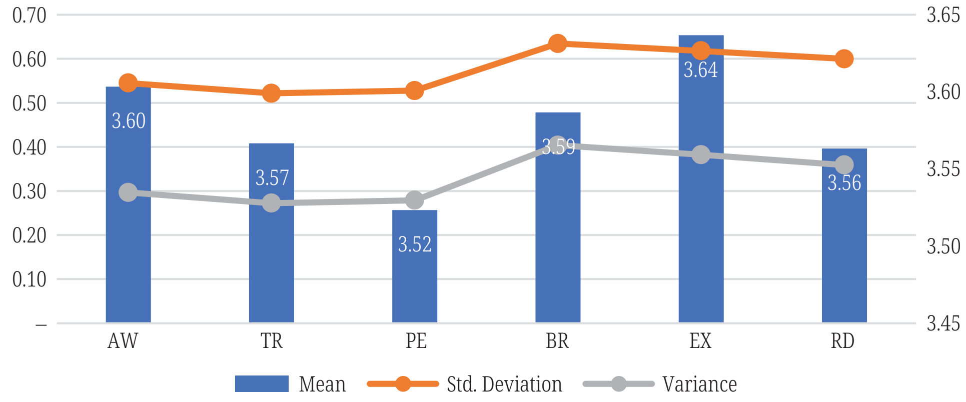

Fig. 6. Descriptive statistics of the AI-based career guidance system

The overall mean score for the AI-based career guidance system was 3.61 on a 5-point Likert scale, indicating a moderately positive perception among participants. This suggests that students generally agreed with the benefits and usability of the AI-based system, although there remains room for improvement in certain dimensions.

As shown in Table A4 (refer to Appendix A), mean scores for the 15 items measuring perceptions of the mobile color vision screening application ranged from 3.51 to 3.67 on a five-point Likert scale, indicating generally positive evaluations from participants. The highest-rated item was CT1 (M = 3.67, SD = 0.579), reflecting strong agreement regarding the clarity, functionality, and ease of use of the application. The lowest-rated items were TC1 and TC3 (both M = 3.51, SD = 0.508 and 0.519, respectively), suggesting relatively lower agreement on certain aspects of the application's testing components.

The overall mean score for the scale was 3.58, reflecting a moderately positive perception of the mobile screening tool. This suggests that students generally agreed on the app's usefulness for preliminary color vision screening and its potential role in supporting educational and career counseling, while also indicating possible areas for improvement in specific testing features. Descriptive statistics for the CVD screening application are summarized in Figure 7, while the full item-level results are reported in Appendix A (refer to Table A4).

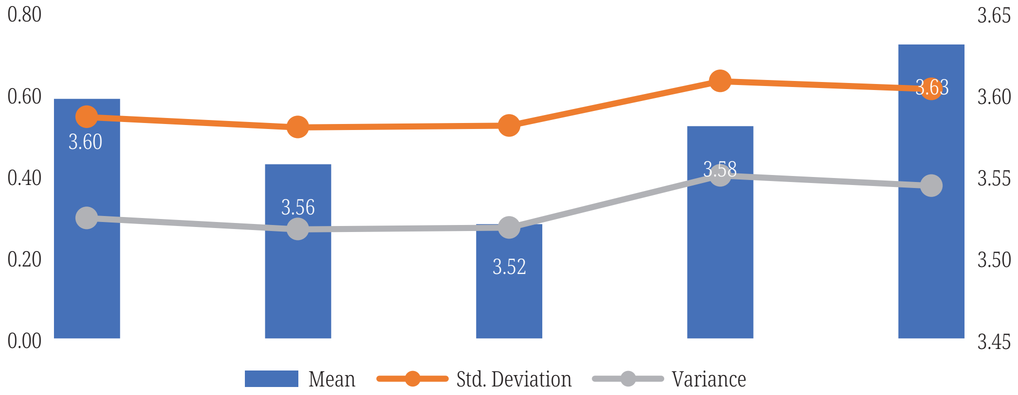

Fig. 7. Descriptive statistics of the CVD screening application

Overall, both the CVD screening app and the AI-based career guidance system received moderately positive evaluations (mean ≈ 3.5–3.6/5), indicating that students generally acknowledged their usefulness while also identifying opportunities for further refinement.

Group comparison. Independent samples t-test results revealed that among the five evaluated dimensions of the mobile color vision screening application, only Quality Assessment (QA) showed a statistically significant difference between the two groups ($t(525) = -2.073$, $p = .039$). Specifically, the mean QA score for Group 1 was slightly lower than that for Group 2 by 0.079 points on the five-point Likert scale (Mean Difference = –0.079, 95% CI [–0.154, –0.004]) (refer to Table 8). This indicates that participants in Group 2 perceived the quality aspects of the application marginally more favorably.

Table 8. Independent samples test for AI-based career guidance system evaluation

Independent Samples Test										
		Levene's Test for Equality of Variances		t-Test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
OS	EVA*	0.676	0.411	–1.318	525	0.188	–0.05362	0.04067	–0.13352	0.02628
	EVNA**			–1.320	447.126	0.187	–0.05362	0.04062	–0.13345	0.02621
QA	EVA*	0.570	0.451	–2.073	525	0.039	–0.07915	0.03819	–0.15417	–0.00414
	EVNA**			–2.085	453.673	0.038	–0.07915	0.03797	–0.15377	–0.00454
TC	EVA*	0.000	0.984	0.157	525	0.875	0.00603	0.03839	–0.06939	0.08144
	EVNA**			0.157	443.439	0.875	0.00603	0.03843	–0.06950	0.08156

(Continued)

Table 8. Independent samples test for AI-based career guidance system evaluation *(Continued)*

Independent Samples Test										
		Levene's Test for Equality of Variances		t-Test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
EF	EVA*	1.163	0.281	–1.073	525	0.284	–0.05125	0.04775	–0.14506	0.04256
	EVNA**			–1.051	413.766	0.294	–0.05125	0.04874	–0.14707	0.04456
CT	EVA*	0.868	0.352	–0.908	525	0.364	–0.04275	0.04709	–0.13526	0.04977
	EVNA**			–0.892	417.659	0.373	–0.04275	0.04795	–0.13699	0.05150

Notes: *EVA = Equal variances assumed. **EVNA = Equal variances not assumed.

In contrast, no statistically significant differences were observed for Overall Satisfaction (OS) ($p = .188$), Test Component (TC) ($p = 0.875$), Effectiveness/Efficiency (EF) ($p = 0.284$), or Content/Clarity (CT) ($p = 0.364$). These findings suggest that, aside from quality assessment, perceptions of the application were generally consistent across the two groups. The results of the ANOVA are provided in Appendix A (refer to Table A5).

Independent samples t-tests were first conducted to examine potential differences in participants' evaluations of the mobile color vision screening application between two demographic groups (e.g., male vs. female). Among the five evaluated dimensions, only QA showed a statistically significant difference between the two groups, $t(525) = –2.073$, $p = 0.039$. This indicates that participants in one group rated the quality aspects of the application slightly higher than the other group. No significant differences were found for OS ($p = 0 .188$), TC ($p = 0.875$), EF ($p = 0.284$), or CT ($p = 0.364$).

Subsequently, a one-way ANOVA was performed to investigate differences among five subgroups (e.g., participating schools). As shown in Table A5, EF was the only dimension that exhibited statistically significant differences among the subgroups, $F(4, 522) = 5.934$, $p < 0.001$. Post-hoc Tukey tests for EF indicated that Group 1 rated the application significantly higher than Group 3 ($p < 0.001$), and that Group 3 rated it significantly lower than both Group 4 ($p = 0.003$) and Group 5 ($p = 0.003$). No other pairwise differences reached statistical significance.

For CT, no statistically significant differences were observed under the Tukey criterion; however, Tamhane's test suggested that Group 1 tended to rate this dimension higher than Group 5 ($p = 0.044$), indicating a possible trend that warrants further investigation. No statistically significant differences were found for OS ($p = 0.278$), QA ($p = 0.979$), or TC ($p = 0.132$).

These findings suggest that perceptions of the application are largely consistent across different demographic and institutional groups, with the exception of effectiveness/efficiency and, to a lesser extent, QA, which appear to vary depending on user characteristics or institutional context.

Overall, the results demonstrate that the developed mobile application achieved high diagnostic accuracy, strong internal consistency, and sound construct validity. User evaluations were generally positive across both the mobile screening tool and the integrated AI-based career guidance system, with only minor differences observed between demographic and institutional subgroups. These findings provide a solid empirical foundation for discussing the implications, limitations, and potential future developments of the proposed system.

Although minor variations were found across demographic and institutional subgroups, students' perceptions were largely consistent, underscoring the broad applicability of the application.

5 DISCUSSION

This study developed and validated an Android-based mobile application for preliminary CVD screening integrated with an AI-based career guidance module. Testing with 527 high school students confirmed diagnostic accuracy, high reliability of the evaluation scales, and generally positive user perceptions, with only minor differences across demographic and institutional groups. These findings extend earlier work on digital CVD tools by demonstrating feasibility in real educational settings and, importantly, by linking screening results with personalized career guidance. This integration highlights the potential of the system as a cost-effective and scalable solution for school-based health and counseling programs.

At the same time, several limitations should be noted. The Ishihara test, while widely used, does not capture all types or severity levels of CVD and may underestimate prevalence. The accuracy of the mobile version depends on smartphone display calibration and ambient lighting, which can introduce variability across devices and contexts. In addition, user feedback was based on self-reported surveys, raising the possibility of response bias, and the geographic focus on Da Nang limits the generalizability of the findings.

Future research should therefore broaden participant diversity across regions, incorporate complementary diagnostic methods beyond Ishihara, and explore adaptive algorithms to reduce dependence on device calibration. Longitudinal studies are also needed to assess whether linking health screening with AI-driven career guidance has sustained impacts on students' academic decisions and occupational trajectories.

Similar evaluations of prototype mobile health applications, such as those for mosquito-borne disease diagnosis, have reported satisfactory diagnostic accuracy and user acceptance [16]. Despite these limitations, the application demonstrates strong scalability potential. Its mobile format, low cost, and AI-based personalization make it suitable for broader adoption, particularly in resource-constrained contexts. For cross-national implementation, however, localization of career guidance datasets and alignment with national education policies will be essential to ensure cultural relevance and equitable educational access.

6 CONCLUSION

This study confirms the feasibility and effectiveness of a mobile application that combines CVD screening with AI-based career guidance. Beyond demonstrating diagnostic accuracy and user acceptance, the system illustrates how digital health innovations can be integrated into education to promote equity and support students with specific needs.

Looking ahead, further development should focus on cross-platform compatibility, integration of additional diagnostic tools, and validation through larger, multi-regional trials. By advancing these areas, the system can evolve into a robust, widely adaptable solution that supports inclusive education and long-term career guidance for students with CVD worldwide.

7 ACKNOWLEDGMENT

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9 APPENDIX A

Table A1. Rotated Component Matrix for AI-based career guidance system

	Pattern Matrix[a]: Component					
	1	2	3	4	5	6
EX3	0.814					
EX1	0.809					
EX2	0.801					
RD2		0.840				
RD3		0.789				
RD1		0.761				
BR2			0.821			
BR1			0.801			
BR3			0.796			
TR2				0.789		
TR3				0.783		
TR1				0.740		
AW3					0.824	
AW2					0.818	
AW1					0.724	
PE2						0.840
PE3						0.789
PE1						0.712

Notes: Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization. [a]Rotation converged in 6 iterations.

Table A2. Rotated component matrix for CVD screening application

	Pattern Matrix[a]: Component				
	1	2	3	4	5
CT2	0.842				
CT3	0.837				
CT1	0.825				
EE2		0.835			
EE1		0.824			
EE3		0.804			
OS3			0.836		
OS2			0.827		
OS1			0.746		
QA3				0.812	
QA2				0.779	
QA1				0.751	
TC2					0.841
TC3					0.807
TC1					0.723

Notes: Extraction method: Principal component analysis. Rotation method: Varimax with Kaiser normalization. [a]Rotation converged in 6 iterations.

Table A3. Descriptive statistics for AI-based career guidance system evaluation

	Descriptive Statistics						
	N	Range	Minimum	Maximum	Mean	Std. Deviation	Variance
AW1	527	3	2	5	3.60	0.542	0.293
AW2	527	3	2	5	3.62	0.542	0.293
AW3	527	3	2	5	3.59	0.551	0.304
TR1	527	3	2	5	3.59	0.529	0.280
TR2	527	2	2	4	3.56	0.505	0.255
TR3	527	3	2	5	3.55	0.531	0.282
PE1	527	3	2	5	3.53	0.522	0.273
PE2	527	3	2	5	3.54	0.546	0.298
PE3	527	3	2	5	3.50	0.515	0.266
BR1	527	4	1	5	3.54	0.596	0.355
BR2	527	4	1	5	3.62	0.623	0.388
BR3	527	4	1	5	3.60	0.685	0.469
EX1	527	4	1	5	3.68	0.592	0.350
EX2	527	4	1	5	3.59	0.615	0.379
EX3	527	4	1	5	3.64	0.647	0.418
RD1	527	4	1	5	3.57	0.594	0.352
RD2	527	4	1	5	3.57	0.609	0.370
RD3	527	4	1	5	3.55	0.596	0.355
Valid N (listwise)	527						

Table A4. Descriptive statistics mobile color vision screening application evaluation

Descriptive Statistics							
	N	Range	Minimum	Maximum	Mean	Std. Deviation	Variance
OS1	527	3	2	5	3.59	0.537	0.289
OS2	527	3	2	5	3.62	0.542	0.294
OS3	527	3	2	5	3.58	0.548	0.301
QA1	527	3	2	5	3.58	0.517	0.267
QA2	527	2	2	4	3.55	0.506	0.256
QA3	527	3	2	5	3.54	0.528	0.279
TC1	527	2	2	4	3.51	0.508	0.258
TC2	527	3	2	5	3.54	0.536	0.287
TC3	527	3	2	5	3.51	0.519	0.269
EE1	527	4	1	5	3.54	0.593	0.352
EE2	527	4	1	5	3.61	0.609	0.371
EE3	527	4	1	5	3.59	0.688	0.474
CT1	527	4	1	5	3.67	0.579	0.336
CT2	527	4	1	5	3.59	0.610	0.372
CT3	527	4	1	5	3.63	0.643	0.413
Valid N (listwise)	527						

Table A5. ANOVA results for group comparisons in application evaluation

ANOVA						
		Sum of Squares	df	Mean Square	F	Sig.
OS	Between Groups	1.064	4	0.266	1.276	0.278
	Within Groups	108.828	522	0.208		
	Total	109.892	526			
QA	Between Groups	.082	4	0.020	0.110	0.979
	Within Groups	97.252	522	0.186		
	Total	97.334	526			
TC	Between Groups	1.312	4	0.328	1.778	0.132
	Within Groups	96.271	522	0.184		
	Total	97.582	526			
EF	Between Groups	6.581	4	1.645	5.934	0.000
	Within Groups	144.735	522	0.277		
	Total	151.316	526			
CT	Between Groups	2.427	4	0.607	2.190	0.069
	Within Groups	144.635	522	0.277		
	Total	147.063	526			

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