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Robotic process automation support in telemedicine: Glaucoma screening usage case

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ABSTRACT

Glaucoma is a worldwide leading cause of irreversible blindness. Early detection is crucial for successful treatment and prevention of vision loss. Recently, tele-ophthalmology has gained more acceptance for remote consulting, and eye screening. The tele-ocular screening can be enhanced further with emerging technologies in robotic process automation (RPA) that offers the ability to automate repetitive human tasks of the ocular screening process. This work aims to assess time effectiveness of the RPA-supported glaucoma screening. Mobile-based glaucoma screening combining RPA and machine learning (ML) is developed for assessing its usability and the time effectiveness of the RPA-supported glaucoma screening. The usability evaluation of the developed application is conducted with 68 participants including both patients and medical staff. Handling times that users spent with or without RPA support are recorded along with the satisfactory questionnaire surveys. The results show that the screening system with integration of RPA reduces the average handling time per user by 75%. The overall satisfaction score of the application is 8.10 out of 10. The machine learning module helps in notifying clinicians when the preliminary diagnosis results in severe conditions, allowing timely treatment. Integration of RPA and ML can assist clinicians and reduce the workload of medical staff significantly. Our study shows that the RPA and ML-based framework improves customer experiences and cost-time efficiency. It promotes feasibility in large-scale population glaucoma screening and data collection.

1. Introduction

The advances of recent technologies in digital retinal imaging, mobile technology, and artificial intelligence (AI) have allowed the adoption of tele-ophthalmology along with traditional medical practices. These technologies enable tele-ophthalmology to exchange medical data and information, screen high-risk cases, assist physicians in diagnosing ocular conditions, and refer patients for in-person follow-ups [1–4]. Tele-ophthalmology provides the solution to deliver better eye care services to remote or underserved areas, and under COVID-19 pandemic restrictions [5]. It also addresses urgent challenges, including the uneven distribution of ophthalmologists within countries and the rise of chronic eye diseases in the aging population. There is additionally a need for more data collection and use of data at national and sub-national levels to generate better policies and provide essential eye care widely.

From the Thai visual impairment project report [6], it is estimated that in 2022 there will be approximately 400,000 glaucoma cases in Thailand. The statistics also indicate that the number of glaucoma patients is increasing every year. Annual eye examinations for early detection and treatment of glaucoma are an essential key to preventing blindness from glaucoma. However, there are a limited number of nationwide eye screening programs. In March 2019, the Thailand Glaucoma Society conducted glaucoma screening. However, there were only 337 participants from all over Thailand [7]. This is due to the problem of nationwide screening for glaucoma or eye diseases, which is costly and time-consuming [8,9]. Moreover, the early detection of eye disease often requires experienced ophthalmologists. During the COVID-19 pandemic, in-person visits for glaucoma screening are even more challenging due to travel restrictions, limited capacity in hospitals, and the concerns of viral spreading. A nationwide eye screening program in Thailand has been postponed for 2 years consecutively during

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the outbreak. However, recent developments and implementations of various tele-ocular screening systems enable medical professionals to remotely monitor and diagnose potentially blinding chronic eye diseases, such as diabetic retinopathy (DR) and glaucoma [10–15]. Tele-ophthalmology has a great potential to provide an accessible and cost-effective solution for screening, diagnosis, and monitoring of glaucoma [16–25].

The development of an efficient and cost-effective tele-glaucoma system is mandated to promote population-wide eye screening. The efficient tele-glaucoma system requires multiple components, as it should be able to exchange medical data, screen high-risk cases, assist physicians in diagnosing glaucoma conditions, and refer patients for in-person follow-ups and care. Patient history should be included in the system for long-term treatment monitoring. The system should provide reliable, cost-effective, user-friendly data gathering, timely and accurately notify users, and be easy to integrate into the related existing systems.

Recently, robotic process automation (RPA) has emerged in several business sectors such as banking, insurance, retail, healthcare, and education [26–29]. RPA is a software application or software robot that is designed to automate defined processes. RPA executes a sequence of steps to emulate human activity and transform data into meaningful information. The following tasks can be conducted by RPA integration as a virtual user: opening a website, logging into a system, sending files, storing and executing data, generating reports, notifying peers, etc. RPA is lightweight and non-invasive as it only accesses the presentation layers of existing applications [30]. Therefore, it can be integrated easily into the existing system with short development cycles, low-cost integration, and accelerated system development.

The effectiveness of RPA in the private health care sector has, for instance, been tested by deploying RPA in the analysis of value-creating functions [31]. According to Refs. [31,32], RPA can increase efficiency in repetitive procedures in healthcare. Leveraging RPA in healthcare can help to reduce time and resources that are required to perform repetitive functions. In addition, it has high potential in increasing job satisfaction and enhancing customer experience. Moreover, RPA offers opportunities to enable faster system, scaling for massive usage such as eye screening, improving cost and time efficiency. Automating workflows of remote monitoring and operation management, such as registration, payment, eye image management and scheduling using RPA, will improve the effectiveness and efficiency of the screening system.

This work explores the use of RPA in eye screening. We developed the mobile-based glaucoma examination prototype with RPA and machine learning (ML) integration in the system. The prototype framework deploys RPA software as a virtual user for gathering data, including patient history, making payments, requesting clinical visits, assisting image acquisition, and transferring medical images and data between an existing central enterprise resource planning (ERP) system and a mobile application. The RPA acts as the intermediary among patients, medical staff, hospitals' existing systems, and the mobile application. The ML modules are integrated within the tele-glaucoma framework to assist ophthalmologists in glaucoma diagnosis. The proposed framework leverages the potential of mobile technology to support data communication among peers, and promotes real-time visualization and user interaction. The developed mobile application is validated through a usability test involving 68 participants including patients and medical staff. The operating time of a glaucoma examination between tele-glaucoma service with RPA support and in-person glaucoma examination is quantitatively measured and compared. The results show that RPA implementation raises the effectiveness of the eye screening system.

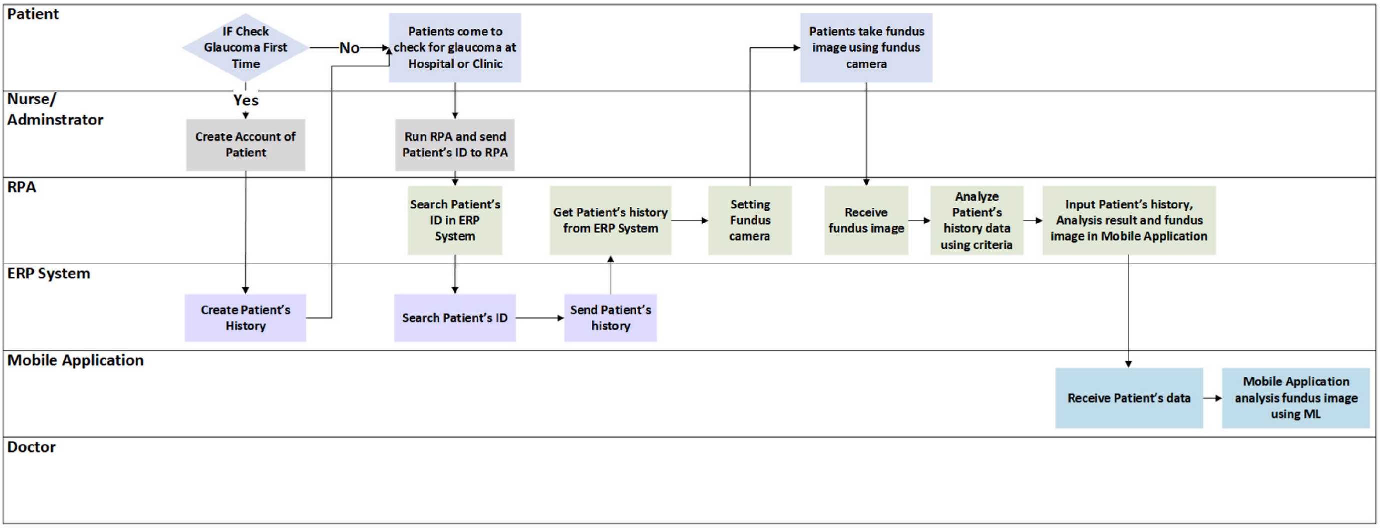
2. Methods

We implemented a pilot project by integrating RPA and ML within the glaucoma screening framework for its usability assessment and time-cycle comparison. The proposed glaucoma screening framework was tested with 68 patients and medical staff of a rural hospital in Thailand. The mobile application with the proposed framework was developed for the Android platform using React Native which included a JavaScript library for building user interfaces. The UiPath Automation Platform [33] was used for RPA system development. The application was designed to store data on a private server, because the hospital where we tested the prototype had already used a private enterprise resource planning (ERP) system for data storage. The basic information of patients, such as patient IDs, patient personal records, or examination histories were already available in the existing ERP system. We only added a table for storing additional information. Exploiting existing data helped us to reduce time in the prototype development and also to maximize the use of existing information. In the long run, it would be more cost-effective than using cloud servers in terms of cost, administration, security, and server size.

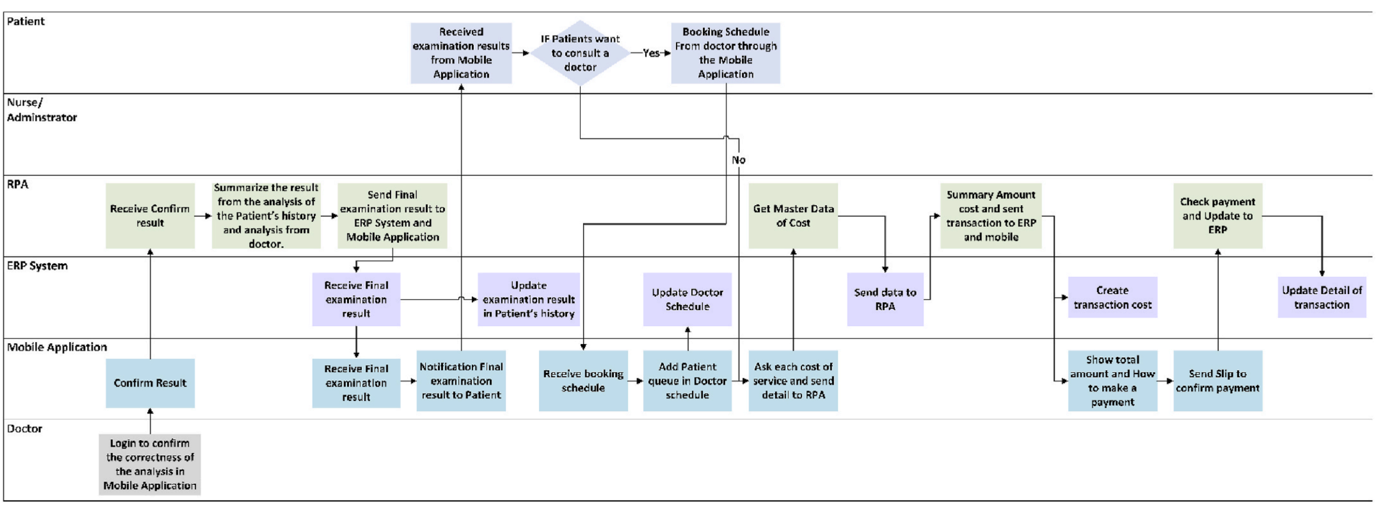
An initial design of an RPA-ML based eye screening was proposed in Ref. [34]. In this work, we further devised additional tasks within the screening system, namely registration, medical appointment scheduling, and payment processing, all of which were facilitated by RPA. The screening application development was focused on facilitating early clinical examinations, including a comparison of analysis results from previous and current examinations of a patient. The patient's examination history was stored in the system to view traceability data.

RPA is a non-invasive software robot aiming to automate repetitive human tasks. Steps to implementing RPA with the system are to identify data and break down each task into process flows, then build and test the robot for each process. Process operations and flows of RPA and its involved parties in our glaucoma screening application are illustrated in Fig. 1. Fig. 1a shows processes before diagnosis confirmation that are automated by RPA. At the first hospital visit, a patient record is created in the existing ERP system. The first-time registration used a manual approach since identity verification in Thailand required face-to-face verification along with the personal identification card. After the first-time enrolment, RPA helped in delivering data, searching, and retrieving patient records. The RPA acted as the intermediary for the transmission and partial analysis of the data, based on computational criteria including a statistical comparison between the previous treatment history and the values measured at the present visit. Fundus images could be taken at both local and remote hospitals as the application allowed users to upload and display them on the mobile application. The system was developed based on a store-and-forward approach. With the RPA integration, fundus images and clinical histories of patients were automatically gathered and submitted to the ML-based glaucoma analysis module. Automating these processes helped to reduce human workload and errors. If the preliminary diagnosis showed that the patient's eye was in a severe condition, the application therefore directly prompted eye specialists for timely verification and treatment. The application was designed to aid the expert in glaucoma diagnosis. Physicians could visualize the fundus images and patients' historical medical records. The application supported the specialists in adjusting clinical parameters, such as OD size before making the final diagnosis remotely. The developed machine learning module for diagnosis in this work was still in an early stage. We included optic disc measurement and the textured-based glaucoma analysis [35,36] within the program.

Processes after diagnosis confirmation that are automated by RPA are illustrated in Fig. 1b. After the diagnosis confirmation from the specialist, the decision results and relevant information on the ERP and mobile application were collected, summarized, and updated. The patient was notified about the results and an appointment for the next examination was then arranged, or a re-imaging was requested if needed. The application also supported payment handling by sending a list of services to the RPA, after which the RPA extracted the master data of each expense from the ERP. The expenses were then summarized to generate the transaction costs to be sent back to the patient. Once the patient had verified the payment via the mobile application, the RPA then checked the transaction and updated the transaction status on the



(a) Task Operations of the RPA: Part 1



(b) Task Operations of the RPA: Part 2

Fig. 1. Task Operations of the RPA and its Involved Parties in the Proposed Glaucoma Screening Application.

ERP.

Since the RPA can be easily integrated with existing enterprise systems, the patient and doctor's examination queue can be put in the hospital enterprise resource planning system. The RPA can work as a middleman interacting between the ERP, the mobile application, and users. This allows physicians to perform scheduling management such as maximizing the number of patients and prioritizing patient queues based on preliminary diagnosis results. Thus, the RPA helps to improve resource efficiency and scheduling management. Notably, the important part of RPA development is to pay attention to data security during the transmission between the RPA, EPR, and mobile. For secured traffic, transmission API is used as a unique token ID that must be sent with each API call to log the call and verify the identity of the call.

Functional and satisfaction questionnaires were conducted. The participants were asked to rate their satisfaction on a scale from 0 to 10, with a score of 10 standing for fully satisfied. The questionnaires covered user satisfaction in three main aspects:

1) Application appearance - including menu layout, text and image placements, color tone, and font sizes.
2) Content coherence and dependency between each user interface window-whether the provided user interfaces offer ease of understanding of the contents that are linked between pages.
3) The completeness of information of the application.

3. Case study and results

Data collection: Observational studies of the mobile application developed with RPA and ML support were conducted at Samut Sakhon Hospital (a local hospital in Thailand). The developed application was used to assess the time-cycle of the RPA-based glaucoma screening system and the practical usability of the proposed tele-glaucoma screening system. Functional and satisfaction questionnaires were collected from 68 users who used the developed application during 3rd-31st August 2020. During that time, Thailand imposed the state of emergency and curfew, but was not completely lockdown. The users included both patients and clinical staff. The questionnaires were considered based on the design, functionality, and the system throughput of the application.

Processing: Survey questionnaires were sent out to patients and clinical staff who used the framework application. Demographic details were recorded. The 68 respondents consisted of 64.7% female and 35.3% male individuals, with different education levels as follows: 30.9% postgraduate, 57.4% bachelor's degree, and 11.7% diploma or lower. An age distribution of the participants was as following: below 25 (8.9%), 26–35 (13.2%), 36–45 (11.8%), 46–55 (27.9%) and over 56 (38.2%). A ten-point scale was used with a score of 10 standing for fully satisfied. The average score and its standard deviation were computed based on demographic features of age, education, and gender.

Results: Table 1 illustrated the summary of the obtained satisfaction scores. Based on the results of the questionnaires, the respondents seemed to be satisfied with the overall application layout. The application appearance, including menu layout, text and image placements, color tone, and font size, received a satisfaction score with a mean of 8.35 and a standard deviation (SD) of 1.13. The mean satisfaction scores on text and image placement, color theme, and ease of menu access were all above 8.1. Coherence of content across different UI pages was scored with a mean of 8.23 and SD of 1.03. The completeness of the information received the lowest mean satisfaction score of 7.9 and SD of 1.07. According to the feedback, more relevant content should be provided, and units of measurements should be added to the application.

The satisfaction score with respect to different demographic characteristics indicated that gender does not show a significant effect on the satisfaction score. The average score of content coherence and dependency decreased with the increase in education and the increase with age below 55 years old. Education level also affects the satisfaction score of the completeness of the information. The higher the education level obtained, the higher the satisfaction score of the completeness of the information.

For the throughput, we collected the operating time of the main tasks supported by RPA and compared it with the operating time spent on traditional visits at the hospital. Table 2 depicts details of the average operating time per task. Note that the average timing of registration is computed from the second time requested services onward. Under the RPA environment, the total operating time was substantially reduced by a total of 75%.

4. Discussion

The main objective of the proposed framework development is to exploit recent advanced digital technologies to improve the feasibility of performing mass ocular screening. RPA has the added value of being integrated into an automatic diagnostic system based on machine learning. It helps to improve the cost-time effectiveness of the telemedicine system. From our observations in a local hospital with decent telecommunication quality, the average time spent on waiting and processing repetitive tasks is reduced roughly from 95 to 23 min (about 75% reduction). The total operating time of each task under the RPA environment can be varied depending mainly on internet access quality and payment verification process.

During the test period, the hospital's main infrastructure for ERP and PC connections was 100 Mbps Ethernet wired network. The hospital also provided Wi-Fi network of 2.4 GHz for internal wireless activities. Unauthorized mobile users commonly used 10 Mbps mobile internet plans. In this work, the payments were verified using OTP (one-time password) protocol which was mostly used in Thailand during the test period. With recent online payment verification such as PromptPay, the completion of payment time could be shortened. In mass screening, a ratio of the number of participants and dedicated ophthalmologists would affect the waiting time for results.

Table 2
Average operating time under manual and RPA environment testing.

Tasks	Manual	RPA
	Operating Time (mins)	Operating Time (mins)
Registration	15	5
Queuing Patients	10	~0
Fundus Image Acquisition	15	5
Waiting for the results	30	5
Scheduling Next Visit	10	3
Making Payment	15	5
Total	95	23

For the system without RPA support, average handing time depends on the number of in-person patients at hospitals, which varies from place to place. In this work, we conducted the test in a local government hospital, which generally received a significant number of patients every day. However, the number of visitors was moderate compared to the number of patients at government hospitals in larger cities. The total operating time of traditional visits could be much higher than 95 min.

Based on our observations, automating repetitive tasks such as patient record transformation and update, fundus images handling, analysis of patient history management, billing, and scheduling using RPA, improved the cost-time effectiveness of the screening system. The RPA freed up time for medical staff and patients.

Furthermore, there was a clear improvement in user experience as the RPA acted as the intermediary entity between multiple caretakers, patients, and systems. Therefore, conflicts among peers during periods of high traffic were reduced. The RPA enabled timely rule-based responses to users. Patients received faster responses and better interactive services. Thus, RPA integration enhanced communication among patients, medical and administrative staff, and the existing enterprise system.

Based on our survey questionnaires on the usability of the application, the user satisfaction rating regarding the design and the functionality of the mobile application was consistently over 81%. The participants could use the application with ease. In our observation, users of age lower than 35 years old give higher satisfaction scores to the overall application. The effects of age on satisfaction score reports a mixed finding. The completeness of information of users aged between 26 and 45 years old gives the average satisfaction score below 7.8. The users of this range of age expect more information. Whereas, users of lower age and higher age expect more on content coherence and

Table 1
Patients and clinical staff functional and satisfaction questionnaire result (N = 68).

		Application appearance	Content coherence and dependency	The completeness of information	All
Age	≤25 years old	8.60 ± 1.48	8.00 ± 2.61	8.33 ± 1.37	8.48 ± 1.63
	26–35years old	8.69 ± 1.00	8.11 ± 2.37	7.78 ± 1.09	8.48 ± 1.31
	36–45years old	8.10 ± 1.72	8.13 ± 1.73	7.75 ± 1.83	8.05 ± 1.71
	46–55 years old	8.34 ± 1.04	8.24 ± 0.97	7.94 ± 1.03	8.13 ± 1.12
	>55 years old	8.32 ± 1.46	8.00 ± 1.68	8.00 ± 1.55	8.23 ± 1.50
Education	≤ Diploma or equivalent	8.26 ± 1.44	8.29 ± 1.10	7.71 ± 1.60	8.49 ± 1.56
	Bachelor	8.21 ± 1.45	8.08 ± 1.71	7.79 ± 1.36	8.13 ± 1.48
	Post Graduate	8.61 ± 1.13	7.95 ± 1.79	8.25 ± 1.33	8.47 ± 1.28
Gender	Male	8.20 ± 1.41	8.27 ± 1.42	8.41 ± 1.14	8.24 ± 1.37
	Female	8.19 ± 1.45	8.60 ± 1.38	8.52 ± 1.32	8.26 ± 1.43
All		8.35 ± 1.13	8.20 ± 1.03	7.92 ± 1.07	8.28 ± 1.41

dependency. The association finding between education level and satisfaction score is more evidence compared to age. The higher the education level, the higher the satisfaction score of the completeness of information and the lower the score of content coherence and dependency.

Based on the obtained feedback, the participants suggested adding more explanations and measurement units to some technical terms. The feedback led to key improvements in the UI design as follows:

- Technical terms in the patient's UI should be replaced with practical terms and explanations that should be easy to understand.
- The mobile application should provide ways for patients to communicate and share their knowledge.

For the eye screening systems to be employed in remote environments with limited resources, the system needs to offer autonomous sample analysis and alerting. Several techniques have been proposed to fulfill these requirements. In our pilot project, we included machine learning-based glaucoma diagnosis [35,36] for completeness of the system. The SVM classifier was used based on fused features and achieved the best accuracy of 87%. The algorithm required adjusting parameters to obtain the best detection accuracy. The ML-based glaucoma diagnosis was gathered along with fundus images, measured eye pressure, and clinical history of the patients collected by RPA to assist in clinical decision-making. In Thailand, the medical diagnosis must always be verified by professional physicians. Thus, an interface for formal investigation, clinical data correction, and approval was included in the proposed system. The survey feedback recommended designing the UI of medical staff and patients to be distinctively different.

Based on the accuracy of the automatic diagnosis obtained, there is a need to improve diagnostic accuracy in our future work. Currently, deep learning (DL) approach has been deemed the gold standard in applying the machine learning (ML) for disease diagnosis. With rapid evolution in glaucoma diagnosis using deep learning and transfer learning techniques, there is plenty of room for algorithm improvements. New transfer learning architectures with high accuracy above 97% are being developed for glaucoma diagnosis [37–41]. However, validation of their applicability for clinical diagnosis is part of the ongoing research. With the rapid advancement of AI technologies in automatic segmentation, detection, and analysis, better algorithms and additional analysis of other ocular diseases can be integrated into the eye screening system in the next version of our application. For this pilot version, we focused on deploying the RPA with the existing hospital system and testing its usability overall. In terms of diagnosis, we included collecting the history of the patient in the time series. Basic structure changes of eyes over very short time intervals were analyzed by RPA. These temporal feature data were very useful for slow-progressing diseases that usually required a longer period before doctors could determine the extent of the disease. In the next revision, the application will be enhanced to incorporate better statistical temporal data, and better ML-based diagnosis to assist the decision-making.

For our future work, we plan to include graphical tools that allow clinicians to modify cup and disc boundaries. The semi-automatic approach will facilitate clinicians to address inaccurate results obtained from the ML module. Furthermore, a massive data preparation of our eye imaging dataset is needed for accurately evaluating deep learning-based glaucoma analysis. We plan to further exploit the potential of the deep Convolutional Neural Network for future revision.

Another aspect of the future work, the geographical data collection and investigation were not included yet in our pilot prototype. With GPS-based mobile devices, the location can be easily determined. The geographical information can be useful for nationwide screening policy management, and also for customized healthcare services. Overall, the integration of RPA and ML provides a more attractive remote eye screening platform. The proposed system integration increases the efficiency and feasibility of performing annual screening and nationwide ocular screening. This user-friendly integration helps the clinical and administrative staff to save time and costs in triaging the patients and reduce the workload. Therefore, they can spend more time managing difficult cases. Furthermore, the simplicity of the system can provide the opportunity to scale up healthcare services in remote areas with limited healthcare resources. On the whole picture, the system has the potential to help early detection of glaucoma for blindness prevention.

5. Conclusion

This work assesses the proposed framework for the glaucoma screening system relying on the integration of RPA and ML concepts. With the proposed framework, a mobile application is designed and developed, and its usability was validated by 68 users during hospital visits at a rural hospital in Thailand. The user satisfaction scores on the design and functionality of the mobile application are over 81%. The application assists the patients as the RPA bots facilitate fundus image acquisition, notification of examination results, scheduling appointments, and making payments. The RPA bots also assist clinical staff and the hospital in processing registration, prioritizing queues, reporting, and transferring data among several tasks and peers in the systems. With the RPA, the average time spent on waiting and processing all tasks under satisfactory telecommunication quality is reduced by 75%. Our studies show that combining RPA with ML to assist medical professionals in glaucoma diagnosis results in reduced cost and operation time. The RPA-ML framework provides efficient resource management and enables the system to be more suitable for massive ocular screening. In the future, we plan to improve the diagnosis techniques by adding statistical data analysis to several processes for higher diagnosis accuracy.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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