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IMPLEMENTATION OF NON-PHARMACEUTICAL INTERVENTION OF COVID-19 IN MRT THROUGH ENGINEERING CONTROLLED QUEUE LINE USING PARTICIPATORY ERGONOMICS APPROACH

Sugiono Sugiono✉
Department of Industrial Engineering[1]
sugiono_ub@ub.ac.id

Willy Satrio N.
Department of Industrial Engineering[1]

Teuku Anggara
Department of Mechanical Engineering
State Polytechnic of Malang
9 Jl. Soekarno Hatta, Malang, Indonesia, 65141

Siti Nurlaela
Department of Urban Planning and Design
Sepuluh November Institute of Technology
Jl. Raya ITS Campus, ITS Sukolilo, Surabaya, Indonesia, 60111

Andyka Kusuma
Department of Civil Engineering
Universitas Indonesia
Jl. Margonda Raya, Depok, Indonesia, 16424

Achmad Wicaksono
Department of Civil Engineering[1]

Rio P. Lukodono
Department of Industrial Engineering[1]

[1]*Brawijaya University*
167 Jl. Mayjend Haryono, Malang, Indonesia, 65145

✉**Corresponding author**

Abstract

The viral transmission in public places and transportations can be minimized by following the world health organization (WHO) guideline. However, the uncertainty in a dynamic system complicates the social engagement to the physical distancing regulation. This study aims to overcome this obstacle in MRT stations and train by developing an adaptive queue line system. The system was developed using low-cost hardware and open-source software to guide passengers using visual information. The system works by capturing seat images and identify the presence of humans using a cloud machine learning service. The physical representation of MRT was translated to data representation using the internet of things (IoT). The data then streamed using an asynchronous API with a representative endpoint. The endpoint is then accessed by a display computer in the destination station platform to provide visual information. The visual information was ergonomically designed with visual display principles, including the minimum content load, layout, color combination, and dimension of contents. The design of the system was evaluated by Markov simulation of virus transmission in train and usability testing of the visual design. The implementation of the system has balanced the queue line capacity in station and crowd spots distribution in MRT. The system was effective due to the visual cortex manipulation by visual information. Consequently, the aerosol and falling droplets' viral transmission radius can be reduced. Accordingly, the chance for airborne transmission can be lowered. Therefore, the adaptive queue line system is a non-pharmaceutical intervention of viral transmission diseases in public transportation.

Keywords: transport ergonomics, MRT, adaptive information, queue line management, visual display.

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1. Introduction

The pandemic period has forced operators of mass transportation modes and the government to issue appropriate policies. The resulting policies must be able to encourage innovation that can reduce or even hold back the number of COVID-19 spreads. Social restrictions in terms of reducing interactions between individuals to slow the spread of the virus have become the new norm. Recent research finds a significant relationship between the frequency of flights, trains, and buses from Wuhan and the cumulative number of COVID-19 cases [1]. Many researchers have explored the potential implications of social distancing on daily commuting patterns. Social contact avoidance can change the amount and type of activities outside the home. According to a health perspective, this principle puts forward the technical requirements regarding operations management, personnel requirements, and health protection in public transport places such as airports, harbor, train stations, mass rapid transit (MRT) stations, and bus terminals. The method of COVID-19 spreading is through droplets, air, surface to surfaces, and facial-oral (The World Health Organization (WHO), 2020). Social or physical distancing, less contact, and ensuring a healthy workplace are the global recommendations to minimize the widespread of the COVID-19 pandemic (ILO, 2020).

Human mobility restriction during pandemics can cause various direct and indirect impacts on humans. Social distancing has a negative impact on mental and health conditions, as it can result in social isolation and limited physical activity [2]. The COVID-19 pandemic caused dramatic effects on international and domestic tourism along with various impacts on certain sectors such as transportation, travel, hotels, restaurants, conventions, and attractions [3, 4]. As social beings, restrictions on social interactions between humans can cause psychological disorders such as depression and delayed mental development in children [5, 6]. Besides that, restrictions on socialization and physical movement during the pandemic have resulted in circadian rhythm disruption and decreased sleep quality [7]. As a consequence, society needs to adapt to this condition. Hence, it is important to create a breakthrough to enforce adaptation in the new living condition.

One way to create a breakthrough is to change the way humans interact in public places. This can be done by the current technological application. The emergence of data science has made data technology applicable [8]. Thus, it is possible to gain insights from physical data. System modeling can be employed to convert the physical data to logical data that able to be processed by computers. Fortunately, today's computer has more than enough capability to process large and complex data. This is also supported by easy internet access in major cities. Therefore, data technology is possible to be applied as a social guidance system in public places to manage social interaction while maintaining health during pandemics.

The possibility of the adaptation only can be judged by applying the social guidance system in public places that are categorized as the point of transmission or hot-spot. During pandemics, public transportation has received a negative perception from society as the virus spreader [9]. This has made the public place that intersects with public transportation a hot-spot. Aside from society perception, the large mass movement in daily public transportation such as MRT, train, and bus COVID-19 transmission is riskier than air transport. IATA study has confirmed that COVID-19 in-flight transmission is low [10]. Long before COVID-19 pandemics, the use of an underground train has been linked with the transmission of infectious disease [11]. The use of an underground train insists people stay alongside other people on the train and repeatedly meet new people. In other words, there is always contact with others before the trip, during the trip, and after the trip. This condition is similar to other daily public transportation such as MRT. Hence in this study, the MRT train and station will be the observed system based on the concerns raised.

On the other hand, the order of passenger traffic when entering and exiting MRT has to be controlled to increase embarkation safety. Many accidents on MRT and other similar transportation embarkation have been reported due to the indiscipline entity in the queue line [12]. However, the safety level of a system can be increased by applying the right preventive measure [13]. In the queue line system, this can be achieved by the application of queuing theory to determine the queue capacity and the safety regulation needed by the system [14]. Even though, the existing system was not ready for instantaneous change due to its role as a system planning tool. Big data applications have been implemented in the urban transport system [15]. However, this implementation has not reached its full potential. This happens because the existing system is unable to evolve immediately following the need for the current situation and condition. Thus, the current urban transport system can't act as a social guidance system.

The social guidance system development in this study is the realization of non-pharmacological intervention in [11] study by a data technology application and as an extension to the system explained by [15]. This study aims to manage the passenger queue line of MRT to increase its queue discipline alongside its safety. This study also promotes the way to adapt to the new public situation during pandemics. The effort to achieve this study goal is through the development of the adaptive queue line system as the social guidance system in the MRT queue line. The adaptive queue line system was designed using a holistic approach. This research continues to improve MRT management, such as: thermal comfort [16], aerodynamic noise [16], and usability tests on the MRT information system during the pandemic. The research provided information for the MRT passengers to select the best queue line in front of the wagon doors according to availability of space. The user interface information of visual display has been built based on the Ergonomics approach, and it employed a usability test. The system successfully showed how to innovate to tackle or to reduce the spreading of COVID-19 virus.

2. Materials and Methods

The adaptive queue line system software, hardware, and the procedures to build the system are presented in this section.

2. 1. Adaptive Queue Line System Hardware

The capacity detection system was built by a microcomputer and IoT cameras installation in an MRT carriage. The microcomputer was Raspberry Pi 4B with a Raspbian buster operating system. The microcomputer task was as a message broker for IoT cameras and the client for a cloud server. The IoT cameras and the microcomputer were communicated using the Message Queuing Telemetry Transport (MQTT) protocol. The IoT camera used was ESP32 Camera consisting of the OV2460 camera module and ESP32-S IoT microcontroller board. The microcomputer and IoT cameras were powered using 12V Battery. The camera was embedded on the ceiling of every seat row. Each camera was assigned with a string address as its MQTT topic. The topic was subscribed by the broker and the target uniform resource locator (URL). The topic was used as a link to send the detection data from the MQTT broker to the cloud server. The train displayed on the monitor was determined by the distance between the station and the train. The train location is tracked using GY-NeoP6MV2 GPS Tracker. The GPS tracker was connected to the Raspberry-Pi microcomputer using a Serial Peripheral Interface (SPI).

2. 2. Adaptive Queue Line System Software

The software of the adaptive queue line system was classified into cloud server software, IoT software, client software, and user interface (UI) software. All of the software used was developed using Python programming language. The cloud application was a representational state transfer application programmable interface (REST-API) application developed using the FASTAPI module. The server was an asynchronous gateway interface (ASGI). The ASGI server was built using Uvicorn as it was bundled with FASTAPI. The cloud server has a role in locating the detection data to the right URL for each seat, priority seat, and hand strap. The file extension of the detection data was JavaScript object notation (JSON) containing the status of the regular seat, priority seat, and hand strap. Following that, the data were temporarily serialized using Pydantic as a database validator module.

The status of a seat, priority seat and hand strap represents its availability. The status was determined based on the result of the image classification. The image classification for seat and hand strap status determination was done using the Clarifai general model. Clarifai is a cloud machine learning service that provides machine learning REST-full service with some predefined models. The general model is a predefined deep neural network model for image classification. Clarifai's general model understands the features of a person. These include the existence of a person in an image, gender, and the priority needs. The input image was an image containing an area that fit an image of a single person. However, the image captured by the camera was a seat row image that contains multiple seats. Therefore, the image was cropped using the python image library (PIL) in the client application. The client application was run on a microcomputer. In conjunction with the image classification task, the client application also has to post the status to the URL specified by each camera MQTT topic to the server. Therefore, the client computer has to subscribe to the topics provided by the camera by running Mosquitto as an MQTT broker application.

The seat status of an oncoming train has to be visible at the next station. Therefore, the URL accessed by the computer on the next station was determined using a distance matrix relationship. The distance matrix API of the Google cloud service was used to measure the distance of a train to the next station. The train was the first point of location input for the distance matrix API and the list of the station data was the input for the second point of location. Hence, the distance between the train and every station in its route was measured over time.

The NMEA satellite signal was used to locate the train. The NMEA signal was decoded through the Pynmea2 module installed in the microcomputer. The train locator client application post current latitude and longitude obtained from GPGGA and GPRMC decoding. The distance between the train and the station was measured in the server by employing the GeoPy module. The distance was measured against all MRT Jakarta Phase 1 Route as listed in **Table 1**. The GUI application on the station displays the train that closest to the station. The GUI application was informed by the server about the distance. Every calculation was done on the server. The GUI application requests the data using the GET method to the server. The server returns the closest train id.

Table 1

Mass Rapid Train Route Phase 1

	Station Name	Position Coordinate (Latitude, Longitude)
1	Lebak Bulus Grab	(–6.2890153530358335, 106.77495228293648)
2	Fatmawati	(–6.292496674449966, 106.79246087484817)
3	Cipete Raya	(–6.278024712127162, 106.79729780992541)
4	Haji Nawi	(–6.2666726828037564, 106.79729406205706)
5	Blok A	(–6.25560268099357, 106.79720291177131)
6	Blok M BCA	(–6.244295561486719, 106.798164082936)
7	ASEAN	(–6.238599350722738, 206.79848509837664)
8	Senayan	(–6.225036984957758, 106.80258179718933)
9	Istora	(–6.222743958008986, 106.8073132650453)
10	Stasiun MRT Bendungan Hilir	(–6.214875348355859, 106.8177463285034)
11	Setiabudi Astra	(–6.2089086775190364, 106.8216970810895)
12	Dukuh Atas BNI	(–6.300554475930085, 206.83379540992465)
13	Bundaran HI	(–6.191614005523534, 106.82302291177074)

The ESP32 camera IoT application has been developed using MicroPython. The MQTT module used was an asynchronous MQTT module for MicroPython. The firmware used for the ESP32 camera was micropython-camera-driver. The firmware was installed to the camera using the esptool python package in a notebook computer run on Ubuntu 19.10 operating system. Each camera represents a seat row or hand strap row. The MQTT topic of a camera was specified based on its seat row or hand strap number. The camera was sent the captured image to the MQTT broker in realtime. The quality of service (QoS) in image data transfer was set to 0 to send only the latest camera capture.

2. 3. Visual Information Design

The seat availability status information was transferred to the passengers by the visual display. The Infographic design and physical system for displaying the visual information were considered.

The infographic was a graphical user interface (GUI) application developed using visual studio 2019 with C# language. The GUI design was started by a layout design. The design principle used was the Gestalt principle to define the layout sequence. The design process was continued by determining the font height and proportion for 10m visibility. The font height was determined using (1). The width, boldness, the distance between fonts, and space distance were determined from its height based on a proportion coefficient. The proportion coefficients were determined by following the guide [17]. The color of the visual information was determined by following web content accessibility initiative guidelines (WCAG) 2.0:

$$\text{font heigth} = \frac{\text{Visual Distance (mm)}}{200}. \tag{1}$$

The visual information was presented on a screen next to a corresponding MRT Carriage door. The screen used was a 32 inch 1080p HD LED screen. The luminance of the screen was 300 nits (1 nits = 1 cd/m^2). The height of the screen was determined using the latest version of Indonesian Anthropometry [18]. The dimensions involved were D2 (eye height) and D9 (eye height in sit position) in the 50th percentile. The screen tilt angle was determined based on the viewing angle requirement for flat-panel display television [19]. Therefore, the tilt angle consideration was ranged from –8° to 8° and the information must be visible for sitting and standing person.

2. 4. Usability Testing

The usability testing was performed to evaluate the ease of use of the system and the user-friendly visual information. The displayed prototype was tested by using a usability approach with 25 respondents. Usability is defined in ISO 9241-11 as the level of user satisfaction, as well as the effective and efficient use of a product by certain users for certain purposes. Usability dimensions need to cover five things: learnability, efficiency, memorability, errors, and satisfaction. The usability test worked on five respondents, [20] stated that 5 respondents would give usability problems finding an average of 85.55 %. The first stage of measuring usability was calculating the learnability of the respondents by giving a test in the form of 2 assignments for each test. The first test was identifying the MRT carriages with the most number of public seats available and the second test was selecting the seat that will be occupied in the selected MRT carriage. According to the collecting data of 5 respondents, the success rate is presented in (2):

$$\text{Success Rate} = \frac{\left(s + \left(p \times 0.5\right)\right)}{\text{Total Task}} \times 100\ \%. \tag{2}$$

The second stage was measuring the efficiency of the respondents to understand the visual display of queue application. As well as the success rate measurement, the efficiency measurement was by giving the respondent the same tasks. However, the quantity measured by (3) is how fast the respondents understand the displayed information:

$$\text{Time Based Efficiency} = \frac{\sum_{j=1}^{R}\sum_{i=1}^{N}\frac{n_{ij}}{t_{ij}}}{NR}. \tag{3}$$

The error dimension depends on the total error of the opportunities number in carrying out those 2 assignments which are the learnability dimension and the efficiency dimension. The opportunities were the rooms to improve the GUI design. To determine opportunities, it is necessary to observe the activities details in using the GUI application. The error rate was quantified using (4):

$$\text{Error Rate} = \frac{\text{Total Defects}}{\text{Total Opportunities}}. \tag{4}$$

The satisfaction dimension was measured by recapitulating the System Usability Scale (SUS) score data to determine the percentile rank score. The formula to calculate the total score of the SUS for each respondent was provided in equation (5):

$$\text{Score} = (Q1-1)+(5-Q2)+\ldots\times 25. \quad (5)$$

2. 5. Non-Pharmaceutical Intervention Evaluation

The viral spread of COVID-19 via direct and indirect transmission can be modeled as a Markov state. The COVID-19 virus can be in one of three possible states. The first state was on the infected or a carrier person's body. The second state was in the indirect transmission state. Indirect transmission happens when the virus spreads across solid surfaces, air, or liquid. The third state was the direct transmission state. Direct transmission occurs when the virus is transmitted from person to person.

As a Markov state, each transmission state transition is only affected by the latest state. There is a probability of state transition for each state. In this model, the state probability was assumed to be fixed. The Markov state transition is depicted in **Fig. 1**. The Carrier Body (CB) probability was determined as an equiprobable state with a slightly higher chance to transmit the virus than re-inhale the virus. The Direct Transmission (DT) state was a state of a non-infected person. Therefore, DT was a passive state because a non-infected person can't spread the virus. The Indirect Transmission (IT) state is a state that represents the COVID-19 virus without a host. Therefore, the virus has the probability to be transmitted to a person, untransmitted, and regained back by the infected person. The regain probability was small because the infected person is in a moving condition.

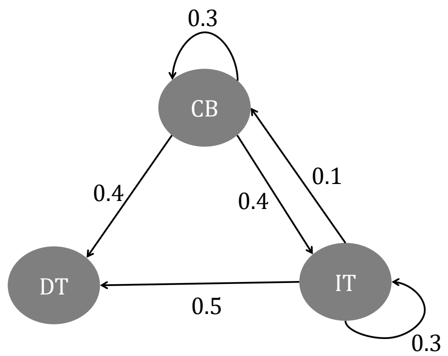

Fig. 1. The States of COVID 19 Transmission in MRT Carriage

The matrix expression of **Fig. 1** is shown in (6):

$$A = \begin{bmatrix} 0.3 & 0.4 & 0.4 \\ 0 & 0 & 0 \\ 0.1 & 0.6 & 0.3 \end{bmatrix}. \quad (6)$$

The probability of a non-transmitted virus was low. The probability of direct and indirect transmission was equal as modeled in (7):

$$\pi_0 = [0.1 \quad 0.45 \quad 0.45]. \quad (7)$$

The evaluation of the process was performed based on the step number taken by CB. The step number of a CB in the existing system is independent. The step number of a CB in the AQLS system was dependent on the success rate of system usability. The higher the success rate the fewer steps the passengers take to find a seat. In this approximation model, a step is a square area as big as the seat.

Therefore, the AQLS non-pharmaceutical activity can be predicted by simple calculation of the final probability matrix with the step number as shown in (8):

$$\left[CB \quad DT \quad IT\right] = \pi_n A. \tag{8}$$

The value of n was the number of the state change. The state always changes whenever CB taking a step. The complete Markov chain result in n cycle was defined as step transmission probability (STP). STP defines the probability of a CB to transmit the virus during each step. STP derived from the equation (8) and calculated using a Python program with the help of the NumPy module. The input of the program is the step taken by CB in an MRT carriage and the approximated number of people met by CB in each step taken. The STP and step number were the basis to determine the predicted transmission in each step (PTS) as written in equation (9):

$$\mathrm{PTS} = \mathrm{Step} - \left(\mathrm{STP} \times \mathrm{Step}\right). \tag{9}$$

The person transmitted by CB can be predicted with the equation (10). The occurrence probability was set to 0.3. This indicates there was a 30 % chance of a person can be transmitted through the change of state. The result was floored to a lower integer value.

$$\text{person transmitted} = \mathrm{PTS} \times \mathrm{Person} \times P_{occurence}. \tag{10}$$

The existing queue line system and AQLS were compared using the constructed models by scenario-based test. There were 10 scenario tests of seat selection by CB in an MRT carriage.

2. 6. Experimental procedures

The research worked in some steps to achieve the goal of crowd management in MRT stations, which are described as follows:

1. Selecting and preparing equipment, e. g. camera to record physical representation of a train wagon.
2. Mapping the MRT carriage physical position to API endpoints.
3. Capturing seat images and identifies the presence of humans using a cloud machine learning service.
4. Posting the data (*c*) to the specified endpoint on cloud server through client microcomputer.
5. Streaming the endpoint data (*d*) using an asynchronous API.
6. Display computers access the endpoint data (*e*) on cloud server.
7. Designing the visual display based on an ergonomics approach.
8. Testing visual display design by usability test based on recapitulating the System Usability Scale (SUS) score.
9. Testing the virus transmission by Markov simulation.

3. Results and discussion

3. 1. The Design of Adaptive Queue Line System

In this subsection, the implementation of the adaptive queue line system design is reported. The system was designed to manage the passenger queue line in front of MRT doors based on a real-time seat availability detection system. The seat availability status of an oncoming train will be served on monitors in front of corresponding MRT Carriage doors. Therefore, the passenger in the queue line knows the position of the available seats. Consequently, the passengers can adjust their position in a queue based on oncoming train capacity.

The adaptive queue line system was implemented in queue line management. The overview of the implemented system was summarized in **Fig. 2**. The passengers in the queue line receive seat availability information from the screen on the platform. Each screen was placed next to each door. The incoming passenger to the queue line will see the screen to find the available seat on the train. This leads to the generation of rational choices for a passenger to queue in a queue line that corresponds to the available seat. Therefore, the adaptive queue line system has a role as a decision support system for the passenger to help the passenger to decide the seat location. The implication of the adaptive queue line system implementation is the increase in queue discipline and safety.

The information that passed from the incoming train to the passengers in the queue line was based on the current status of the seat availability. Therefore, the status information sent to the passenger has to be the latest seat status. As shown in **Fig. 2**, the physical representation of the current status was modeled into a data representation. The data representation was modeled as close as possible to its physical representation by mimicking the train modularity with the «has a» relationship. The parent object that has the children object relationship is limited by «one to many» relationship. This will convert the data from the train to representative information that able to be mapped into a specified URL in the cloud server. Then, the information will be displayed on the screen.

The status information was determined by the seat availability detection system. The seat availability detection system has the responsibility for feeding the seat images to the Clarifai general model and processing the resulting output. As a multiclass classification model, the Clarifai general model generates more than one output. The output consists of the probability value and the predicted concept as the data label. As illustrated in **Fig. 3**, the predicted concepts were checked by the keyword lookup. In case one of the conditions in keyword lookup is true, then the seat is taken. These lookup conditions were determined using predefined keywords. The predefined keywords are people, person, man, and woman. In **Fig. 3**, the classification result shows people, woman, and man in predicted concepts. Hence, the seat is taken and the status data was sent to the seat URL.

The result of the train positioning on the client application consists of GPS Geocodes. The result of train position tracking displayed on a microcomputer console using a GPS tracker can be seen in **Fig. 4, *a***. As shown in **Fig. 4, *a***, the latitude and longitude data always displayed after the device received GPRMC and GPGGA geocode message. Whenever the device was unable to receive the signal, the read error message will appear.

The train position data will be posted to the server to determine the destination station based on the order in **Table 1**. The destination data format is shown in **Fig. 4**, ***a*** after the latitude and longitude lines. Those data were accessed through an URL with a «/destination/» endpoint. The destination was saved in the station data table as the JSON data. The station data table is then accessed by the GUI application in the destination station to get the train id. The MRT Carriage information of the train with the corresponding id is displayed in the visual display. This process is schematically figured in **Fig. 4, *b***.

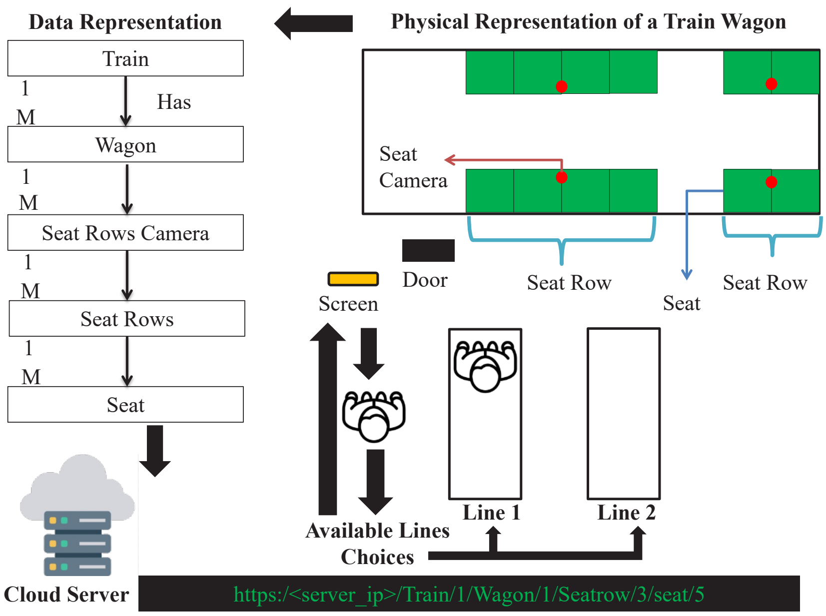

Fig. 2. Overview of the adaptive queue line system

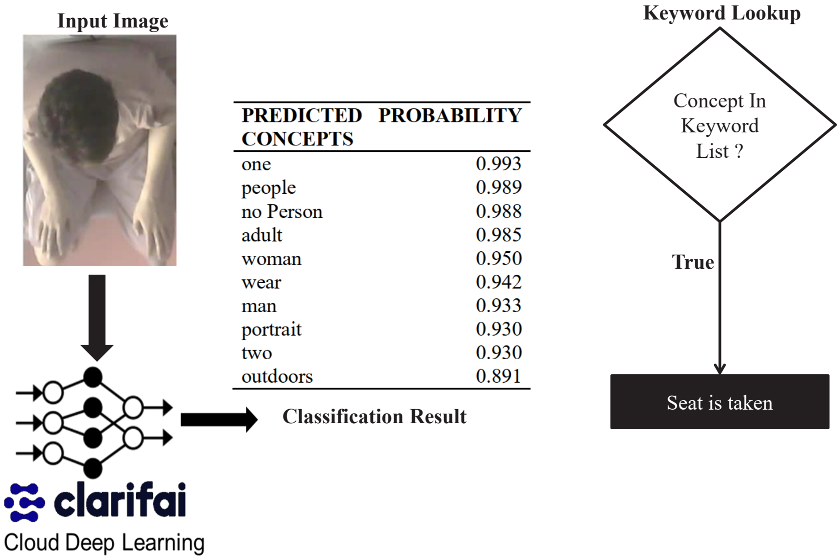

Fig. 3. Seat availability detection mechanism

Fig. 4. Positioning System: *a* – Client GPS; *b* – Destination determination

3. 2. Visual Information Display

The infographic has to be easy to understand by the passengers. Therefore, a neat and tidy layout is needed to deliver visual information. This intended to make the passengers in the queue line easy to find narrative hints in the displayed infographics while maintaining visibility in the long-range. The narrative hints in the information are the collection of symbols that are grouped [21].

As seen in **Fig. 5**, the visual information of the adaptive queue line system was displayed while maintaining its simplicity. The standard collections of symbols are used to represent the system. This collection of symbols consists of lines, rectangles, and circles. The grouped lines were representing an MRT Carriage. The rectangles with rounded ends were representing the seat. The availability of the seat was represented by its color. Red indicates a seat was taken, light blue indicates a seat is available; black indicates a seat is not available due to physical distancing, and a stronger blue represents a priority seat. The circle between the rectangles represents the location of the hand strap for the standing passenger.

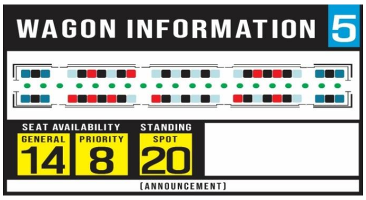

Fig. 5. Visual Information in the queue line

The text information was presented under the MRT Carriage image. The current capacity of each seat type on an MRT Carriage is displayed using text. Therefore, the font height was determined based on the visual distance using (1). Font height is the height of the uppercase character measured from the descender line to the ascender line. The results of the calculation are presented in **Table 2**. The presented results were the roundup of the maximum visual distance as an input to the (1). The required font height was directly proportional to the visual distance. The visual distance is the distance between the object and the eye. As the distance gets farther, the required height is getting taller.

Table 2
Recommended font heights

Visual distance (mm)	Font Height (mm)
<500	2.5
501–900	5.0
901–1,800	9.0
1,801–3,600	18.0
3,601–6,000	30.0
6,001–10,000	50.0

The height of the font becomes the parameter for other font visual attribute sizes. The other font visual attributes are determined using certain proportion coefficients to the height. The width, height, thickness, and distance between lower cases and upper cases for 6 m and 10 m visual distances were determined. The results were presented side by side in **Table 3**. The 6 m and 10 m visual distances were chosen according to the distance between the edges of the MRT platform and the gates to the platform. The information on the screen has to be visible from that distance. At least, the fonts, shapes, colors, and icons are distinguishable. This requires scaling the font while keeping its legibility. This can be achieved by keeping the font x-height to baseline ratio to make sure the typeface consistent when scaled. The consistency also includes the arrangement consistency which determines the clarity of the information provided by a text [22]. When the fonts have been scaled the distance between the fonts in a word and distance between words has to be maintained. Hence, the font height was the only parameter used to determine other visual attribute distances such as width, thickness, and distances to maintain consistency.

Table 3

Font visual attributes on 6m and 10m visual distance

Visual Attributes	Formula	Size (mm)	
		6 m	10 m
Font Height (H)	Eq. (1)	30	50
Upper Case Width	2/3H	20	33.3
Upper Case Thickness	1/6H	5	8.3
Lower Case Height	2/3H	20	33.3
Lower Case Width	2/3H	13.3	22.2
Lower Case Thickness	1/6H	3.3	5.55
Distance Between Upper cases	1/4H	7.5	12.5
Distance between Upper Case Words	2/3H	20	33.3
Distance Between Lower Case	1/4H	5	8.3
Distance Between Lower Case Words	2/3H	13.3	22.2

3. 3. Usability Test Result

The usability test of the AQLS system has overviews the system implementation. The result of the usability test with 25 respondents is shown in **Fig. 6**.

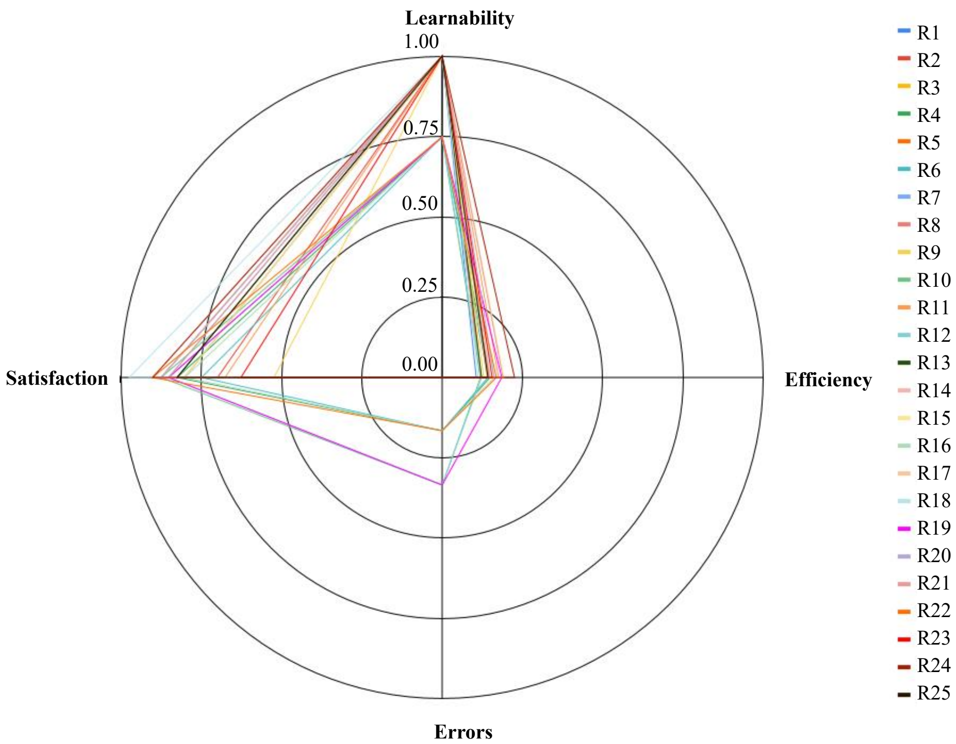

Fig. 6. Respondents Usability Test Results

The learnability of each respondent measures the adaptability of the system. Respondent $R1$ is 60 years old and $R2$ is 59 years old are the older respondents with lower learnability. This indicates the age of the users affects the adaptability of the system. The older respondents are less adaptive to the system than the younger respondents. Even if each respondent only makes one error during the test, the satisfaction score of $R1$ and $R2$ (57.5) is lower than other respondents. On average, all the respondents delivered a satisfaction level of SUS score = 73. Based on the SUS score classification, ergonomically, it can be classified in a good application. A deep interview with respondents showed some recommendations for better usability performance, there are: (1) priority seats can be clarified, (2) the symbol size is not large enough, and (3) the neatness of writing can be improved. Thus, there is some room for improvements available to increase the effectiveness of the AQLS system.

Besides the effectiveness, the efficiency of the usability is crucial in quick interchange systems such as the MRT Queue line. The amount of time the passengers in the queue line needed to understand the seat or standing spot position to target defined as the efficiency of the AQLS system. For example, $R1$ understands the first task in 11.41 s and the second task in 8.84 s will have efficiency = 0.108 goal/s. In the same way, the average of efficiency to learn the tasks for 5 respondents = 0.126 goal/s. As shown in **Fig. 6**, the efficiency of the system is centered towards 0.0 because the shorter the time it takes to understand the task the higher the efficiency to understand the system.

3. 4. Non-Pharmaceutical Intervention Effectiveness Evaluation

The objective of the AQLS system design is as a participatory ergonomics system with an engineering control to minimize virus transmission. Some entrance scenarios were evaluated using the Markov chain prediction approach to model the decision of the passengers. The cases are listed in **Table 4**. The passenger decision modeled in **Table 4** is a CB. Case 1 to 6 is a normal case in which a CB walking towards a seat or a standing spot in one direction. Case 7 and 8 are a special case that models a CB that unable find a seat because all the seats were full. Therefore, the CB has to find a standing spot. Likewise, cases 9 and 10 also modeled the two-directional movement of a CB inside an MRT carriage because a CB drops its phone near door 3 or seatrow 7. The target location is the final destination of the CB.

Table 4
Test Scenario

Case	Special Case	Target Location	Entrance (existing)	Step	Entrance (AQLS)	Step
1	–	Seatrow 2 seat 1	Door 1	10	Door 2	3
2	–	Spot 12	Door 2	8	Door 3	4
3	–	Seatrow 2 seat 1	Door 1	10	Door 2	3
4	–	Spot 12	Door 2	8	Door 3	4
5	–	Priorityrow 3 seat 3	Door 4	25	Door 1	2
6	–	Priorityrow 3 seat 3	Door 4	25	Door 2	2
7	Full seat	Stand spot 10	Door 1	21	Door 4 (Seatrow 3 seat 7)	3
8	Full seat	Stand spot 11	Door 2	21	Door 4 (Seatrow 3 seat 7)	3
9	Drop The Phone	Seatrow 3 seat 5	Door 2 (Drop on Door 3)	25	Door 4 (Drop on Seat 7)	7
10	Drop The Phone	Seatrow 3 seat 6	Door 2 (Drop on Door 3)	25	Door 4 (Drop on Seat 7)	7

The result of implementing AQLS is a better decision to choose the entrance with a minimum distance to the target location. The entrance chosen by passengers in AQLS is assumed to always have the shortest path to the target location. This also represents the passengers with perfect learnability in understanding the system usability. These better decisions are represented by the number of steps taken by a passenger to the target location. In the case of CB, the numbers of the steps determine the contact of a CB to another passenger. More steps mean more contact with another passenger. Therefore, the chance of a CB to transmit the virus to another passenger is defined by the entrance selection.

The Markov chain was used to evaluate the virus transmission chance based on the number of steps of a CB and the possible numbers of contact in each step. The number of steps in **Table 4** was plugged into equation (10) to calculate the possible number of persons transmitted after made a contact with CB. The result of the Markov chain simulation is served in **Fig. 7**. The predicted transmitted person in the existing queue line system is always higher than the AQLS. Hence, successful AQLS system implementation is important to build safer and healthier public transportation.

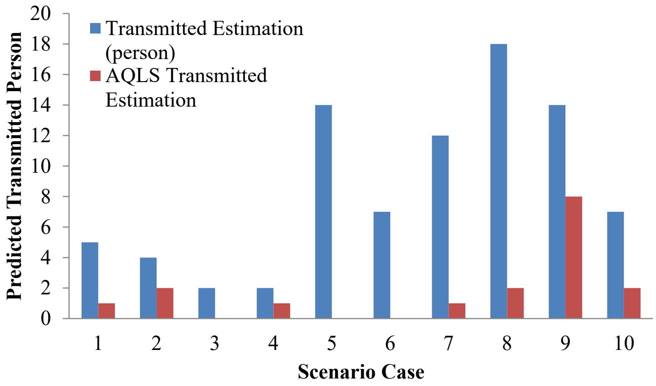

Fig. 7. Comparison of the transmitted person in the existing system and AQLS

The adaptive queue line system ensures the certainty of the queue line capacity and the seating capacity to reduce physical contact of passengers during pandemics. The seat availability information guides a passenger to a specific seat or hand strap in the MRT carriage. As a result, no seat or hand strap searching process will be performed by the passengers inside the MRT. The uniformity of the queue line also can be assured. This because the seat maps information of an MRT Carriage is displayed on the queue line. Therefore, the passengers will decide to embark on the train through the nearest door to a chosen seat or hand strap. The decision to move to the next MRT Carriage only available if the MRT Carriage already reaches its maximum capacity. This is strengthening the physical distancing regulation during the pandemics. Moreover, the implementation of the system will also prevent queue lines from overload.

The adaptive queue line system key role is as a non-pharmaceutical intervention for disease transmission. COVID-19 can easily be transmitted in the crowd without physical distancing regulation. The air around an infected person is concentrated by the virus [23]. The virus will spread through aerosol under the physical distancing distance range. As the virus is attached to a micro-droplet, it is carried by the droplet and follows the parabolic motion of the falling droplets. This can infect sitting passengers by an infected standing CB or by a CB that is searching for a seat inside an MRT carriage. As illustrated in **Fig. 8, *a*** the sitting passengers are in the falling droplet area. The worse scenario is a standing CB can transmit the virus to two sitting passengers as illustrated in **Fig. 8, *b***. However, the falling droplet area radius is dependent on the ejection force magnitude of the Droplet. Thus, the adaptive queue line system can be effective to minimize the COVID-19 transmission in MRT by aerosol and falling droplets.

In conjunction with aerosol and falling droplet transmission, airborne disease transmission possibility has been minimized through the implementation of an adaptive queue line system. Balancing the number of passengers during embarkation can reduce the transmission radius. Without this, some spots on MRT will look like as on the left side of **Fig. 8, *a***. The effect of grouping people together as in the left side image of **Fig. 8, *a*** is not only widening the transmission radius but also has an impact on the higher possibility of airborne transmission. The whole MRT Carriage virus concentration in the air can be raised if the crowds are formed in more than one spot inside an MRT Carriage. This phenomenon can only be avoided by non-pharmaceutical interventions. This is because the dynamics of the system can't be controlled over time due to the existence of some uncertainties [24]. Corresponding to that, the adaptive queue line system is designed as a guidance system to keep the passengers engaged with physical distancing regulation. Hence, the non-pharmaceutical intervention role of the adaptive queue line system can be achieved only if the passenger is willing to use the AQLS.

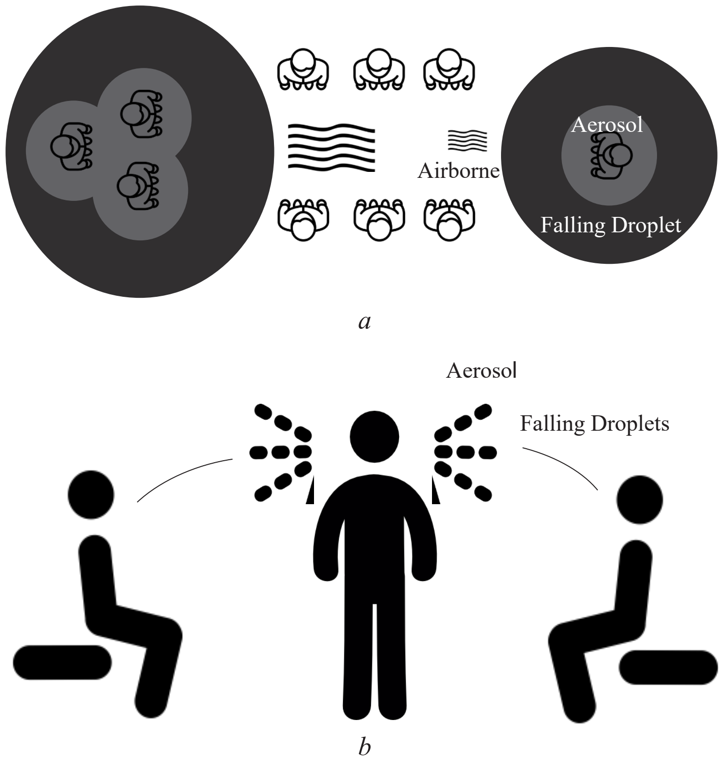

Fig. 8. Illustration of diseases transmission on MRT: *a* – Top view; *b* – Front view

The result of the usability test proves that AQLS is a usable system. The high learnability implies that AQLS is an easy to master system. The only factor that slows down a new user learning process is age. This is shown by an error that was made by the older respondent when identifying seat position from the monitor. Previous study on the effect of age in cognitive ability showed no differences in the learning rate of younger and older respondents [25]. However, aging declines the spatial and visual pattern recognition ability [26]. Therefore, there is a room for improvement in GUI visual design. Information triggers are needed to improve the learning process of the passengers when using the system for the first time. The addition of information triggers such as user guides or an administrative procedure to use AQLS system should be able to maintain the efficiency while increasing learnability.

The efficiency of the AQLS system depends on the respondent learnability. The speed of acquiring information until it is learnable is defined as learning efficiency. Similar to learnability, the learning efficiency of a respondent is also affected by age. The older respondents have some difficulties recognizing patterns on time. Even though the respondents are able to distinguish lines and graphics in GUI visual display. Therefore, the image clarity of the GUI components is unable to accelerate the spatial and visual pattern recognition process. Regardless of that, the usability test was only conducted once. As a result, the effect of the task repetition was not included in this study.

The efficiency of a task completion must be followed by the effectiveness. The task must be done correctly to be able to achieve the initial goal. The effectiveness metric is the error that is measured based on the incorrect result of each task that was completed by each respondent. There is only one respondent that successfully completed all tasks correctly. However, all respondents are having no past experience of using a smart queue line system such as AQLS. The respondents were still able to manage to perform some tasks correctly without repetition and past experiences. This indicates the learning curve of the AQLS system is shallow for the majority of users.

The high satisfaction of the AQLS system portrays the user acceptance. Usability satisfaction dimension measures how far the user expectation of the system and the actual system. Based on the results, the learnability score determines the satisfaction score. The decrease of learnability score is followed by a decrease in satisfaction score. Hence, the satisfaction score can be decreased as the age of the users increases. Although the satisfaction score is lower, it does not mean the older users do not want to use the AQLS system. As a mathematical model, the satisfaction formula does not count user excitement to learn the system. Therefore, there is a bias in the satisfaction score. The real condition is all respondents are showing excitement to learn the AQLS system. Hence, this study reveals the limitation of usability testing to evaluate the system.

The user's willingness to use the designed system was not considered as an input to the satisfaction formula. In fact, the user engagement can be predicted based on the willingness. Current usability testing models only focus on the task completion by the users. There are no variables that correspond to user engagement. Therefore, the low satisfaction score can have an alternative meaning. The alternative meaning is the user is still in the introductory phase to the system. In this phase, the user is building the understanding of the system. At this stage, the user engagement or willingness to use the system is still unknown but the conclusion has been enforced through mathematical calculation of satisfaction score. Therefore, the usability testing objective to learn about the user is not achieved at this point. However, the other usability test objectives are still achieved. The usability test of the AQLS system is still able to uncover system design problems and discover opportunities to improve the system design.

The non-pharmaceutical intervention of AQLS has been proven effective according to the Markov chain simulation result. The steps taken by a passenger inside an MRT carriage can be used as a physical contact indicator. In each physical contact, the virus can be transmitted directly or indirectly. By assuming a passenger as a CB, the input for the Markov chain simulation is the number of steps and number of persons contacted with a CB inside an MRT carriage. As a rough approximation, the simulation results are consistent throughout all tested scenarios. This consistency is achieved by assuming each passenger in the queue line is engaged to use the AQLS system. This means every passenger pays attention to the information displayed on screen. Each passenger chooses the entrance based on the information provided on screen. As a result, the Markov simulation result implies that the non-pharmaceutical intervention role of AQLS system only will be achieved through correct implementation of the system.

The usability test result shows that the excitement of the passengers to use the system is not directly correlated to the correctness of the AQLS system implementation. Passengers may eager to use the AQLS system even if the passenger does not understand the system or is still learning the system. This will result in an ineffective non-pharmaceutical intervention role in the early stage of the AQLS implementation. The only factor to improve correctness of the AQLS implementation is the passenger motivation. Personal motivation is driven by the perceived value [27]. Therefore, each individual passenger has a unique perception of the AQLS implementation. This is the challenge that needs to be overcome in AQLS implementation. Nonetheless, the Markov simulation has predicted the positive outcome when passengers follow the visual information guide.

The information provided on the screen is the guidance to the passenger decision-making. Visual information is known to manipulate brain neural circuitry that is involved in decision-making [28]. The human visual cortex can process information without involving the higher-level area of the brain [29]. This implies the faster classification and recognition of an object or a situation can be triggered by visual stimulation. Therefore, the queue line can be managed adaptively and adjusted with high discipline based on the visual information provided. The provided information has become the guidance to maintain the queue line discipline while adjusting the position.

In this study, the graphical user interface (GUI) has been ergonomically designed based on the user experience principle according to ISO 9241 guideline (ISO Ergonomics of human-system interaction, 2018). Therefore, the presented visual information can be absorbed with the minimum content load by the passengers in the queue line. The minimum content load of visual information is important for the adaptability of the system. As a consequence, the optimum tradeoff between the contrast and the visual information content of the GUI has to be determined. These optimal attributes will ease the queue line adaptation for the passenger.

The change of visual distance affects the visual perception speed and visual display information clarity of text information. This because, the main feature that determines a font shape is its x-height to baseline ratio [22]. The change of ascended and descended height of the font will make the font appear thinner. As a result, a font of a character in the middle of a text will have a greater distance. This will lead to a different perception and enforce re-recognition because the visual style of the information has been changed resulting in decreased clarity. The increase in x-height of a sans-serif font increases its visual recognition speed [30]. Therefore, the proportion coefficients in table 3 were determined based on the visual perception speed and information clarity consistency.

The easiness of the passenger adaptation in the queue line implies a higher safety level in the queue line. This is due to the visual stimulation response as a parameter of time to take action [31]. The time to take action will be reduced if the passengers easily understand their position and direction in the queue line. The action of the passenger is to decide to move to the desired location according to visual information guidance. The displayed visual information has been designed to direct the passengers to the minimum capacity location. As a consequence, the passenger traffic around the platform is able to be balanced. Passenger traffic balancing reduces the meeting chance of the disembark passengers from the train and embarked passengers. This is useful to reduce the spread of the virus during pandemics. That way, the non-pharmaceutical intervention of the system will be as effective as the Markov chain simulated result. Alongside that, the adaptive queue line system has the potential to reduce accidents on the MRT door.

Overall, the AQLS system has been proven advantageous to minimize crowd formation inside MRT and in a station. However, this system is still in an emerging phase. More tests and evaluation in system effectiveness during operation is needed. In conjunction with it, the evaluation of individual passenger response to the visual information provided by the system is important. Therefore, the analysis of individual behavior of a passenger should be performed in the future. Evaluation of passenger engagement to the system is continuously needed. Hence, the adaptability of the system needs to be extended to develop a successful participative system. In addition, the evaluation of AQLS system effectiveness in minimizing virus transmission is also still in simulated form in this study. In future study, the real evaluation must be strived.

4. Conclusions

This study has successfully demonstrated the development of an information system for pandemic widespread prevention and improving MRT mass transportation safety. The adaptive queue line system will ensure the number of queues in front of the train doors at the destination station platform. Furthermore, this queue will reduce passenger traffic and crowds on the train due to seat searches. The integration of ergonomic, data technology, and information technology in the areas of visual display design, user interface experiences, IoT, asynchronous APIs, cloud computing, and machine learning have realized this information system. The adaptive queue line system is a non-pharmaceutical intervention of viral transmission disease inside and outside MRT by maintaining each passenger engagement with the physical distancing regulation using a real-time visual information guide that balances the queue line capacity and the distribution of the crowd spots.

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