Analytics-driven Visualization on Digital Directory via Screen-Smart Device Interactions

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***Abstract*—Informative directories have always responded to a fundamental need of humanity: providing available information around people. However, the escalating amount of content to be visualized on directories makes relevant information search extremely time-consuming. Meanwhile, digital displays based on screen-smart device interaction become an emerging interface of smart services to deal with daily-life challenges like information seeking. Also, multimedia content, such as movie, can be understood by multimedia analytics for recommendation, but there is no effective way to visualize the content of a directory. This paper proposes a novel directory visualization framework— Analytics-driven dynamic Visualization on Digital Directory (AVDD): understanding user preferences via smartphone-based interaction and optimizing visualization by visual analytics in terms of high content relevancy and screen utilization for advanced directories. With experiments in laboratory and real-world settings, AVDD is proven to be effective for visualizing directory with screen utilization over 98% and the score for Likert-scale surveys achieving 73% on average in movie directory.**

***Index Terms*—directory, customized visualization, multimedia, screen-smart device interaction**

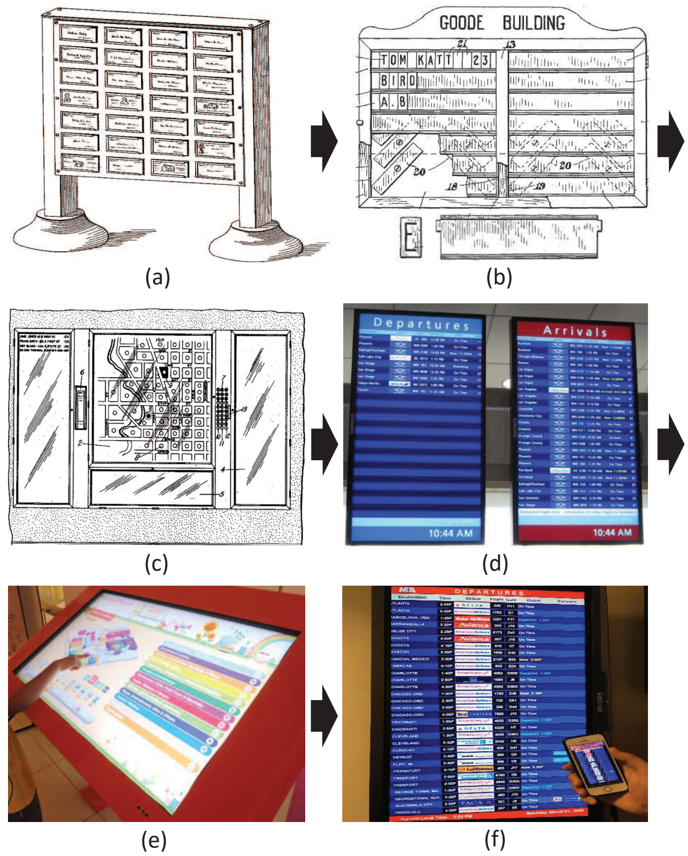


Fig. 1: Evolution of Directory: (a) physical directory, (b) changeable letter sign, (c) interactive physical directory, (d) digital directory, (e) interactive touchscreen directory, and (f) digital directory with smartphone interaction [4].

I. Introduction

DIGITAL environments enriched with the mature deployment of mobile devices and digital displays pave the way for enabling mobile users to interact with visualizing resources [1][2][3]. Smart mobile devices (smartphones) with various sensing and communication capabilities are promoting that mobile users connect each other and to ubiquitous computing devices for socialized and smart services in their daily lives. The digital displays to effectively bring digital content into physical worlds are increasingly becoming pervasive and thus important technology for facilitating smart screen-based services. Hence, interactions between mobile users and displays facilitate sharing content and contextual data of users as well as nearby places. The display systems could play the role of seams between cyber and physical worlds.

Traditional digital displays are found in various (semi-) public locations such as stores, restaurants, movie theaters, university buildings, airports and onboard seats, transportation and its stations, hotels. As such digital displays are mostly connected to the Internet, and thus they access information servers and Web services to show a wide range of information such as transportation schedules, weather forecast, local news, and on-going events as well as various multimedia content such as images, videos, maps, and navigation. For example, it is possible to understand a movie with multimedia analytics, and match the interests of users. It has long been used on social media for recommendation. However, the information and multimedia content are simply listed in a static directory where information and content are displayed in constant forms service providers pre-organized. In other words, this static directory of information and content is visualized on a digital display as a traditional directory on a physical advertisement typically respond to guide users what available around them.

Digital display systems provisioning relevant information and multimedia content on a specific place became already one of the most important daily applications [1][2]. For example, in a restaurant, a user may just want to see the dishes that they are interested, while in a shop, they just want to see the items. With the advance in computer vision and multimedia analytics, understanding dishes [5] and items [6] is possible nowadays, and more information could be provided to users. However, typical display systems relying on such static directory suffer from increasing information and content since more and more materials are being available along with deployment of social media running on smartphones and adaptation of big data techniques. Even using the advanced computer vision systems, such content overload phenomena makes the information search very difficult and highly time-consuming, e.g., finding the right dishes when you are at the cashier. [7] emphasized that a user should be able to pick which information is relevant in “three seconds" if the content of a display is informative, and it is proved that more alternatives cause a user harder decision making [8]. That is, although the main goal of an informative directory is to guide people at a place, the visualization approach leads to restriction in helping people find relevant information and content.

Based on these observations, this paper proposes a smart informative content visualization framework to reflect the trends and needs of this era, named Analytics-driven dynamic Visualization on Digital Directory (AVDD). AVDD exploits data analysis of users such as user preferences for content and intensity for interaction with on-site screens, which are derived from interaction with the user smartphone. These data can be delivered from users’ mobile devices. Based on the analytics on user preferences, AVDD fulfills visual analytics for customized content and screen-optimal visualization. Namely, AVDD improves the current regular directories through smartphone-based interaction with digital displays for customized and optimized provisioning of relevant information and content to users. The empirical research in user and service provider perspectives proves it by the score achieving 73% on average of Likert-scale surveys that AVDD provides high-level readability and quality of user experience. Also, optimal visualization is proven through screen utilization over 98%.

The rest of the paper is organized as follows. Section II addresses the background and the related work. Section III introduces the AVDD framework, and then cloud-assisted computation for optimized visualization with experimental results is presented in Section IV. In Section V, two practical surveys are conducted and discussed to prove the proposed information visualization. Finally, Section VI concludes this paper and presents future work.

II. Related Work

This section provides analysis on visualization systems based on smartphone interaction in two configurational features, i.e., hardware (architecture) and software (content provisioning), and lacks of existing schemes.

A. System Architecture and Interaction

Pervasive visualization resources, i.e., digital displays, could be tightly coupled with pervasive computing resources. As a result, the digital display systems rely on their functional servers and cloud computing systems [3][9], which support content storages or complicated operations. Those displays can also integrate with third-party applications, such as social network services (SNSs) and Web services [10], in which social contextual information and multimedia content are available. The designed systems in [11][12][13][14] took both extensions, i.e., functional servers and cloud computing systems and third party APIs, so they could offer more flexible and comprehensive content display services dealing with a variety of context and content.

Different technologies have been used to create interactions with a display, such as QR code [15], WiFi [3], Bluetooth [13], iBeacon [16], NFC [17], etc. In a higher level, mobile devices such as a smartphone, which provide mobile interaction between its owner and its touch screen in any place at any time [3][18], have been mainly used to enable such interactions. As becoming ubiquitous, such smartphones allow versatile interactions with digital displays[19]. One advantage is that several people can interact simultaneously without obstructing the main screen. People feel more confident when interacting with a display from a certain distance [14]. The study in [10] additionally involved a user monitoring system for investigation of user reactions and behaviors such as passive users, their reflection in the window, and so on. [20] and [21] were designed for particular purposes to provide the adaptive scrolling scheme for collaborative digital newspapers and the smartphone-based marking technique for direct control of the content on a large digital screen, respectively. [3] presents a cyber-physical system whose content can be directly sent to smartphones when users do an an intuitive “dragging” hand gesture with their smartphones, and [22] raises the idea of smart digital signage able to spread its content by cascading from one seed smartphone to others. [9] and [23] propose new interactions between smartphones and digital displays for creating, exchanging and sharing content at a location.

B. Content and Visualization

Digital display systems obtained user-generated information and multimedia content from the third party applications, and they processed system-generated (mixed) information and content based on contextual data for customization with a user or/and a place through functional servers or cloud computing systems [3] [9] [10] [11] [12] [13] [14] [20] [21]. Along with the recent trend of increasing usage of social information of users for customized services such as context-aware social matching [24], content and multimedia provisioning via digital displays shall be fulfilled with adaptive and customized visualization to each user.

For example, in [12], the content (text and photo combined) comes from a social network that can provide data about the location enriched with user feedback. In [11], the user generates content by interacting through a touchscreen. [25] proposes a system where text coming from user smartphones is displayed on a screen. In [10], the content is images coming from Flickr. Finally, [26] emphasizes the fact that the content should come from both user and information provider in order to get suitable information about available transportation and on-coming events at the location. The information or content is visualized on the digital screens. However, all the systems relied on the static forms that service providers pre-allocated and pre-designed. That is, the information and descriptions of multimedia content are simply listed as physical directories, and thus it means the visualization systems have such inherent problems about information searching.

Although [13] and [27] considered adaptive display by user context, they merely extended the tag-cloud concept with simple user information (some of object context of users) for display of text or pictures, or used the presence history of Bluetooth devices for dynamically formatted for display of current status of connected devices with known device owner's photo. That is, it merely displays simple information at one screen and does not consider optimization of screen space utilization or personalized content display which is one of the most important concerning points by user side [1]. In addition, [28] provided a prototype of a public display system with dealing with screen utilization. However, it was merely developed for a single digital screen as the standalone system.

Displays have deployed at diverse places and in many cases the display systems at a place rely on multiple screens. Moreover, displays in public places such as bus stations, airport, etc. and even in private areas like home are employed by multiple users simultaneously. Thus, the display systems should have scalability and extensibility for multi-user and multi-display. Based on our investigation, the current systems are mainly intermediate stages of technology evolution from single-user and single-display to multi-user and multi-display.

C. Analytics for Recommendation

Public displays are known to suffer from display blindness [29], e.g., a lack of interest from people passing. Research conducted to improve the awareness and engagement around the display, by considering the display as a means of discovering a location and creating socialization [30] [31]. Personalization is closely related to recommendation, which provides content/information that is likely to be interested by a user. Recommendation can be based on user interests [32], collaborative knowledge [33] and more [34]. These methods provide ways to evaluate how likely a piece of information/content will be preferred by a user. Recent image-based analytics research [35] has proved that user generated images are able to tell the gender and relationship among users. With the huge amount of images taken by users on their smart devices, it provides an opportunity to personalize recommendation of social media data, but it is not adapted for customized content visualization and screen utilization to match users' interests yet.

Directories have been evaluated from physical directories to digital directories along with the evolution of content changeability and user interactivity, i.e., from constant content to changeable content and from non-interactive media to various interactive media, as shown in Fig. 1. Observations derived from the investigation on recent studies of directory displays based on digital screens reveal novel interactive environments between directories and users through smart mobile devices, or smartphones. The smartphones are not only enriching human-machine interactivity but also enabling new interface between physical and cyber worlds such as QR code [15], WiFi [3], Bluetooth [13], iBeacon [16], NFC [17], etc.

However, such recent smartphone-based interactive technologies for directory displays are still staying at the early stage where constant content and static visualization are merely supported. In addition, there are many works on recommendations and understanding users by multimedia content, but lacks of works on how to display relevant content effectively; there is no consideration of customization for multi-users to increase the quality of user experiences. Therefore, the main contributions of this novel study could be summarized as follows: 1) customized directory visualization based on analytics of user preferences and relevancy to content on a directory and 2) the optimized layout for directory visualization to achieve high screen utilization and content display precision. In addition, to measure user experience quality as well as content provider's intention, two real surveys are fulfilled.

Fig. 2: Current vs. customized visualization for (a) movie and (b) event directories.

III. Proposed AVDD Architecture

AVDD aims to give advanced visualization with analytics for customized directory services. The following scenarios show how AVDD helps users to find relevant information related to a location and conditions. Fig. 2-(a) considers directories of restaurants. If user interests are known, e.g., their preference on the social media, the area of more relevant pictures can be bigger. In addition, as shown in Fig. 2-(b), the visualization of a list of events can be customized to match the cultural background of a user and the timing of each event. Such a customized visualization can help users find interest information at a location by giving greater prominence to more relevant information, while displaying the other information, but smaller. It is firstly described from its architecture and software design, and then each component is studied in detail.

A. Architectural Overview

The upper part of Fig. 3 shows the system architecture of AVDD. It mainly involves the following: 1) smartphones, 2) digital displays, 3) visualization units; 4) a cloud-based analytic system.

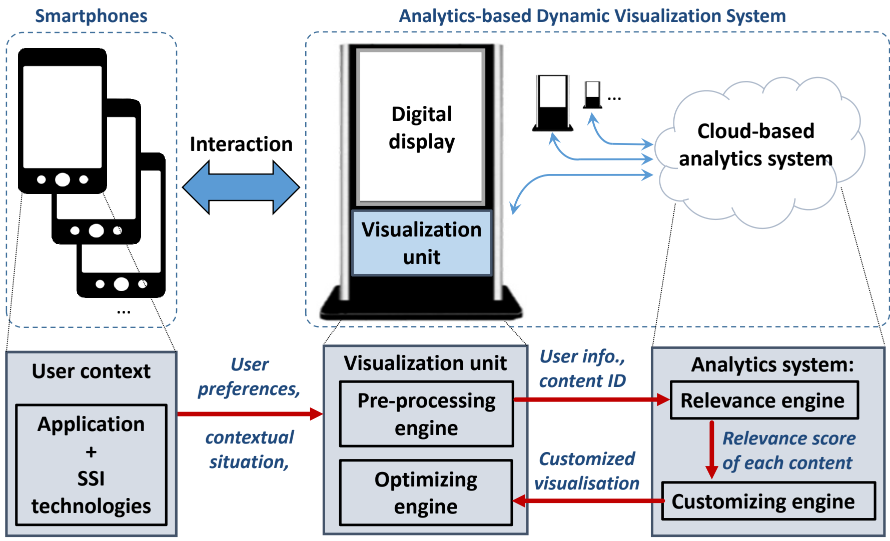


Fig. 3: AVDD framework architecture including screen-smart device interaction (SSI) and analytics-driven visualization

Smartphones are increasingly considered as the most common interface method for screen-smart device interaction (SSI). Here, they are used to collect user preferences and to identify user viewing intent by sensors in the smartphone. Always accompanying their owners, smartphones with SSI technologies are able to collect user information. In AVDD, such SSI is fulfilled and user context derived from the interaction are addressed as follows:

- **Smartphone-based Interaction:** As displays become ubiquitous, it is not rare to see multiple displays within a small area. Since smartphones have embedded SSI technologies as well as sensors, some work like [3] explains that it is possible not only to predict which display users want to interact with, but also to carry out interaction with the display. Such approach is used here: When pointing a smartphone toward a display in AVDD, the smartphone sends user preferences and contextual situation to the visualization unit since the smartphone user tends to look for content in the display.
- **User preferences:** They are learned from user interest, based on his/her age, gender, personality, job and so on, and from his/her behavior. The images in the smartphones also provide some of the information [35]. Such preferences are collected by designing a specific application, using smartphone sensors, or social media.
- **Contextual situation:** Data about the contextual situation could be location-based user information, schedule-based user information, and so on. For example, in a movie theater, this contextual situation is the show time and movie genre. By such user context, people can receive a customized directory visualization service for the movie directory in the movie theater.

B. Analytics-driven Visualization System Components

1) Pre-processing Engine: As the available content on each display depends on the physical locations (e.g., outside a movie theater or a bus stop) and the time (e.g., movies that are showing now or routes that stop at this bus stop), the information of the content such as the content ID is sent to the cloud-based analytic system with the user context. The cloud-based analytic system contains all other information such as the properties of the content so there is no heavy traffic between the unit and the analytic system.

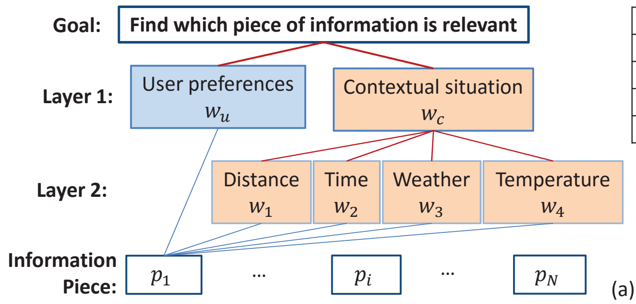
2) Relevance Engine: The proposed system focuses on how to visualize the information based on the relevancy. Relevancy calculation based on the information provided by the user, i.e., user preferences and contextual situation, is fulfilled. The analytic hierarchy process based multi-criteria ranking (AHP-MCR) approach is adopted to demonstrate the idea. In this section, the structure of content is firstly presented, and then a relevance algorithm is proposed for a single user and extended to multiple users.

As previously explained, information from user smartphones can be classified into two categories: user preferences and contextual situation, divided into sub-categories. This hierarchical structure can be used to evaluate the relevance of content displayed on a directory by using an AHP-MCR approach [36], which can find the relative importance of each criterion in given scenarios (looking at a movie directory, a restaurant directory, etc.). A simplified model is presented in Fig. 4 and described below:

- **Goal:** defines the objective to achieve, e.g., find relevant information pieces.
- **Layer:** The different layers and sub-layers correspond to the different criteria and sub-criteria to achieve the goal. For clarity, only the second layer corresponding to a contextual situation is displayed on Fig. 4.
- **Information Piece:** represents the different information pieces that can be relevant.

Considering N information pieces displayed on a directory. Based on AHP-MCR, the relevance score of a particular information piece p_i for a user j, $s_i^{(j)}$ is defined as:

$$s_i^{(j)} = w_u^{(j)} \times s_{u_i}^{(j)} + w_c^{(j)} \times s_{c_i}^{(j)}, \tag{1}$$



	Distance	Time	Weather	Temperature
Distance	1	3/1	1	1
Time	1/3	1	9/1	9/1
Weather	1	1/9	1	1
Temperature	1	1/9	1	1

	Total (Sum)	Weights
Distance	5	0.17
Time	19.33	0.63
Weather	3.11	0.10
Temperature	3.11	0.10

(b)

Fig. 4: AHP model and weight estimation: (a) AHP model, (b) pairwise comparison and weight estimation.

where $s_{u_i}^{(j)}$ and $s_{c_i}^{(j)}$ are two scores from how much this information piece matches the user preferences and from how much it matches the contextual situation, and $w_c^{(j)}$ and $w_u^{(j)}$ their respective, and normalized, weight as shown in layer 1 of the AHP model. As well, layer 2 decomposes $s_{c_i}^{(j)}$ as follows:

$$s_{c_i}^{(j)} = \sum_{t=1}^{q} w_t \times v_{t_i}, \tag{2}$$

where q is the number of type of contextual information (time, weather, temperature, etc.) and $(w_t)_{t=1}^{q}$ their respective weight. The score $(v_{j_i})_{j=1}^{q}$ of each type of contextual information is given using some similarity measures. For example, if two movies are available, then the one starting first will get a bigger value for the "time" parameter. Pairwise comparisons using the 1-9 scale, where 1/1 means that the two elements compared have equal importance and 1/9 means that the second element is extremely more important than the first one, can be used to find the proper weight of each criterion. Fig. 4-(b) shows an example of calculation for layer 2, where the different values of the pairwise comparison matrix can be provided directly by users or learned from their activities. Afterward, the sum of each row is calculated (column "Total") and then the weights are computed as the sum of the corresponding row over the total sum. Finally, if N information pieces $p_1, ..., p_N$ are displayed on a directory, the score vector $\mathbf{s}^{(\mathbf{j})}$ for a user j can be written as:

$$\mathbf{s}^{(j)} = (s_1^{(j)}, s_2^{(j)}, ..., s_N^{(j)}). \tag{3}$$

Finding which information pieces are relevant to a group of people falls within the purview of group recommendation. Aggregation of ratings for individuals is adopted as it can easily accommodate dynamic groups of people and easily extended from the relevancy calculation for one user. Considering that m users $u_1, ..., u_m$ are simultaneously interacting with AVDD, and that N information pieces $p_1, ..., p_N$ are displayed on the directory, the score matrix $\mathbf{s}$ can be written as follows:

$$\mathbf{s} = \begin{array}{c} \\ u_1 \\ u_2 \\ \vdots \\ u_m \end{array} \begin{array}{c} \begin{array}{cccc} p_1 & p_2 & \cdots & p_N \end{array} \\ \begin{pmatrix} s_1^{(1)} & s_2^{(1)} & \cdots & s_N^{(1)} \\ s_1^{(2)} & s_2^{(2)} & \cdots & s_N^{(2)} \\ \dots & \dots & \dots & \dots \\ s_1^{(m)} & s_2^{(m)} & \cdots & s_N^{(m)} \end{pmatrix} \end{array} = \begin{pmatrix} \mathbf{s}^{(1)} \\ \mathbf{s}^{(2)} \\ \cdots \\ \mathbf{s}^{(m)} \end{pmatrix} \tag{4}$$

where $s_i^{(j)}$ is the normalized score of the i^{th} information piece, p_i, given by the user j. If $m = 1$, then the score matrix, $\mathbf{s}$, is equal to the score vector, $\mathbf{s}^{(1)}$, defined in Equation 3. From s, the next step consists of aggregating the relevance scores from the m users of each information piece into a final relevance score. Such an aggregation requires exact understanding grouping conditions at a location. Here, two different grouping types of locations are considered:

- **At transit location:** A group of people has individualistic preferences (goals) and thus some sets of individuals in the group can be considered according to same preferences. Therefore, an information piece relevant to a set or even an individual within a group is dealt with simultaneously. Since the location should be separately recognized, this transit location l is defined as l = 1.
- **At destination location:** Directories are mainly designed to enable one social group (friends, family, etc.) to search for information that may interest the group as a whole. So, l is defined as l = 2 to indicate this case.

Therefore, the relevance score s_i of an information piece p_i can be computed with l as:

$$s_i = \begin{cases} \max_{j=1..m} s_i^{(j)} & \text{when } l = 1 \\ \frac{1}{m} \sum_{j=1}^{m} s_i^{(j)} & \text{when } l = 2 \end{cases} \tag{5}$$

The proposed system is not limited by how the relevancy is calculated. Once the relevancy is calculated, this approach can be applied to find the relevancy of each piece of content to the users. By making use of such relevance scores, the customizing engine dynamically customizes the visualization of information.

3) Customizing Engine: This customizing engine customizes the visualization from information relevance, which is computed beforehand by the relevance engine to displaying relevant information bigger. One of the solutions is tag-cloud, as shown in Fig. 2-(b), a visualization technique giving greater prominence to words that appear more frequently in a source text [37], which the size of a tag influences the number of glances as well as the ability to remember it [38][39][40]. Making relevant content bigger can help people when searching for information. The customizing engine firstly implements a linear function that gives a size to an information piece proportional to its relevance score.

4) Optimizing Engine: As the size of the display is limited, the unutilized display area has to be minimized. It is an information placement problem, where the area of each information

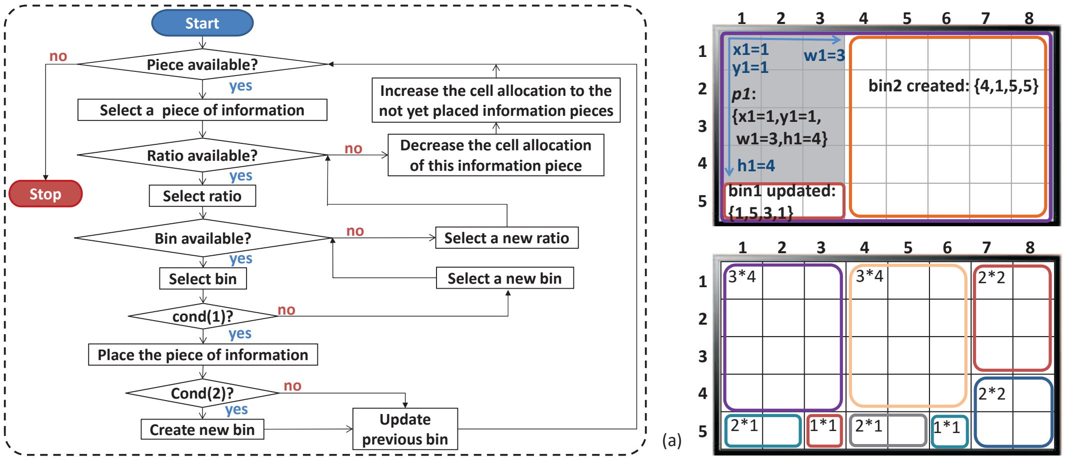


Fig. 5: The placement algorithm and placement examples using algorithm 1: (a) algorithm, (b) placement of the first piece of information, (c) an optimized layout with an 8x5 grid and 8 pieces of information.

should be proportional to the relevance, while keeping the total size of all areas less that the total size of a display. After the customized visualization is calculated on the analyzing cloud, it is then sent to the optimizing engine. The optimizing engine maps the content ID to the details of information, such as the show time and a poster of a movie. In addition, this optimizing engine deals with the precision of visualization. It means that the list of information are precisely ordered along with high relevancy even though they are optimized for utilization. In the next section, a three-step optimized visualization framework is thus introduced to display relevant information prominently while ensuring full utilization.

IV. Optimized Visualization

For optimized visualization, relevance scores of information pieces are processed first, and the problem of minimizing the unutilized area is formulated as an optimization problem. An area is then allocated to each information piece that are afterward placed on the display.

A. Relevance Scores Processing

The relevance scores reflect user context, such as user preferences. According to their respective scores, a particular area is assigned to each information piece. However, such an area is limited by the areas of the display and of the other pieces, meaning that it can not be guaranteed that a particular piece can have its "own" area from its score. Meanwhile, some of the scores are very close to each other, so it does not make much sense for them to differ a lot in the area. Therefore, score processing ensures that the scores are really representing the practical preferences of users as well as taking care of the practical constraints of the display and the feasibility of the optimization problem. If $s_{0_1}, ..., s_{0_N}$ is denoted as the normalized scores of N information pieces before score processing, the new scores $s_1, ..., s_N$ are computed as follows:

$$s_i = (1-\alpha)s_{0_i}^{\lambda} + \alpha, \tag{6}$$

where λ is a positive number and α is a number in [0,1] and both can be adjusted to make the optimization problem feasible. The first part, $(1-\alpha)s_{0_i}^{\lambda}$, makes the more relevant information more obvious by setting the λ greater than 1. The second part, α, can guarantee the minimum size of a piece of information, which the relevant information is not too small to be seen. The choice of α is a more from a system factor. From empirical studies, it is concluded that $(\alpha = 0.3, \lambda = 1)$ and $(\alpha = 0.3, \lambda = 2)$ can be suitable when the scores follow a uniform and a Poisson distribution. These two distributions are considered here because of their “physical meaning": The Poisson distribution may represent the relevance scores at a transit place as only a little information is relevant while the rest is totally irrelevant; The uniform distribution may represent those at a destination place as people are likely to have large preferences.

B. Self-allocation Algorithm

Once the score processing is done, the following optimization problem is run. The objective is to minimize the unutilized display area. N information pieces have to be placed in the display area A. $s_1, ..., s_N$ and $a_1, ..., a_N$ are the scores sorted from highest to lowest and the area given to each information piece $p_1, ..., p_N$. The optimization problem can be written as follows:

$$\begin{aligned} \text{minimize} \quad & A - \sum_{i=1}^{N} a_i \\ \text{subject to} \quad & \sum_{i=1}^{N} a_i \leq A, \\ & a_i \geq \mu, \; i = 1, \cdots, N, \\ & \Delta a_i \geq \Delta s_i \times a_i, \; i = 1, \cdots, N-1, \\ & \Delta a_i \leq 0 \;\text{ if } \Delta s_i = 0. \end{aligned} \tag{7}$$

In this formulation, the first constraint ensures that the sum of the area of the information pieces can not be larger than the display area. The second constraint makes sure that a minimum area, μ, is guaranteed for each information piece. The score variation between two consecutive information pieces p_i and p_{i+1} by $\Delta s_i = \frac{s_i - s_{i+1}}{s_i}$ is defined: if the score of two consecutive information pieces is the same, then the variation has to be equal to zero; If s_i is close to zero, the area a_i should be close to μ. The variation in the area is defined by Δa_i as the difference of area: $\Delta a_i = a_i - a_{i+1}$. The third constraint guarantees a difference of area between two consecutive information pieces based on Δs_i, and the last constraint makes this difference smaller than or equal to zero if they both have the same score. The next subsection introduces how this optimization problem can be solved.

C. Information Placement

The optimization problem that consists of the objective function in (7) and the constraints are known to be a linear programming (LP) problem, which can be solved efficiently by various LP solvers. The optimal result assigns an area to each information piece, which then has to be placed in the display (referred to this procedure as the information placement). Bin packing approaches have been used to solve similar problems, but they are known to be NP-hard and may not be reliable for real time applications [41]. Here, the grid layout which is mostly utilized for information directory in regular shapes and the most practical approach to display content including textual information [42] is exploited. To overcome the restriction of regular-shape visualization of content, proposed framework takes into account irregular layout to provide the customized content visualization. Then, it aims at achieving high utilization and precision of content display.

Grid Design Approach and Cell Allocation: A grid is characterized by the number of rows n_r and columns n_c ($n = n_r \times n_c$ cells) where a cell is considered as the smallest unit to display an information piece p_i. A number of cells c_i is allocated to p_i according to its optimized area a_i. Such an allocation has to conserve the original shape/ratio of p_i. The possible cell allocations can be represented by integers, and are denoted by the set C. Integer $i \subset C$ if $\exists$ a $k \subset \mathbb{Z}^+$ such that $i = r_i K$, where $r_i \subset R$. $R = \{r_1, r_2, ..., r_i, ...\}$ is the set of all possible ratios for given content and directory. For a row directory, a row is dedicated to one information piece, and only the height of the row can be adjusted ($n_c = 1$) and $C = \{1, 2, ..., n_r\}$. For a grid directory, it is important to conserve a ratio close to one of the information pieces, for example, if the information has to be displayed in $1:1$, C can be chosen as follows: $C = \{1\ (1 \times 1), 4\ (2 \times 2), 9\ (3 \times 3), ...\}$. The cell allocation is described in Algorithm 1: a first allocation distributes cells over every information piece according to its area and a second allocation ensures that the total number of available cells n is used.

Placement: Once cells are allocated, the information pieces are placed in the display, as described in Fig. 5-(a). Each piece is placed in the top-left corner of a bin, and a bin can be created or updated. bin_i can be defined as $\{X_i, Y_i, W_i, H_i\}$, where X_i and Y_i are the horizontal and vertical positions from the top-left corner respectively and W_i and H_i are the width and the height of the bin respectively (the unit is the number of cells). For example, bin_1 is written as $\{1, 1, n_c, n_r\}$. Similarly, an information piece p_i is defined as $\{x_i, y_i, w_i, h_i\}$. The framework works as follows: The first bin bin_1 is initialized. The information piece with the higher cell allocation, p_1, is placed in this bin. More generally, an information piece p_i is placed in a bin bin_j if $cond(1)$ is satisfied:

$$cond(1) : w_i \leq W_j \text{ and } h_i \leq H_j, \tag{8}$$

where w_i, W_j, h_i and H_j are respectively the widths and the heights of p_i and bin_j. If $cond(1)$ is not realized, then a new bin is considered. If no bin can realize $cond(1)$, then the ratio of p_i is changed. If no other ratio is available, then the cell allocation c_i of p_i is decreased to the first value of C smaller than c_i and the remaining cells are allocated to the next information pieces p_k, $(k > i)$ by using the second part of Algorithm 1. If $cond(1)$ is realized, then p_i is placed in the top-left corner of bin_j. p_i is then equal to $\{X_j, Y_j, w_i, h_i\}$. A new bin is created if the following condition is satisfied:

$$cond(2) : w_i < W_j, \tag{9}$$

where w_i and W_j are the widths of p_i (placed in bin_j) and bin_j respectively. A new bin is thus created if the width of p_i is strictly smaller than the width of bin_j, and bin_j is updated, as follows:

$$new : bin = \{X_j + w_i, Y_j, W_j - w_i, H_j\}. \tag{10}$$

$$update : bin_j = \{X_j, Y_j + h_i, w_i, H_j - h_i\}. \tag{11}$$

ALGORITHM 1: Cell allocation

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Data: p_1, ..., p_N: set of N information pieces
      a_1, ..., a_N: area of p_1, ..., p_N
      C: list of possible cell allocations
      n: total number of cells
Result: C = {c_i}_{i=1}^N: cells allocated to p_1, ..., p_N.
/* first allocation                                   */
inter ← 0;
for i ← 1 to N do
    c_i = ⌊a_i × n / Σ_{i=1}^N a_i⌋;
    if c_i = 0 then c_i = C_min while c_i ∉ C do
        c_i = c_i − 1;
        inter = inter + 1;
    end
end
/* second allocation                                  */
r ← n − inter; j ← 1;
while r > 0 and j ≤ N do
    c_j = c_j + r;
    r = 0;
    while c_j ∉ C do
        c_j = c_j − 1;
        r = r + 1;
    end
    j = j + 1;
end
```

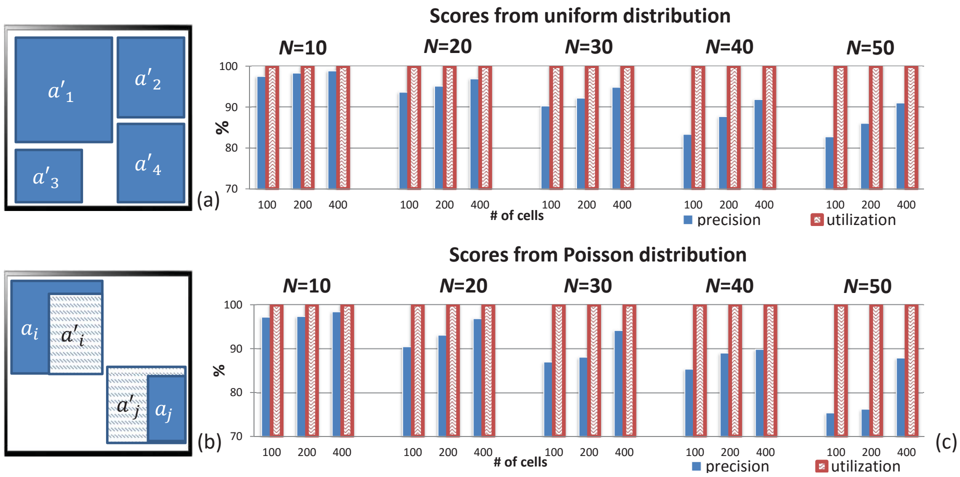


Fig. 6: Precision and utilization from normal and Poisson distributions: (a) utilization, (b) precision, (c) evaluation.

If $H_j - h_i = 0$, then the bin is full and can no longer be used to place information pieces.

Fig. 5-(b) shows the placement of p_1 (12 cells) on an 8×5 grid for a grid directory. bin_1 is initialized to $\{1, 1, 8, 5\}$. Two ratios r ($1/2 \leq r \leq 2$) are available for p_1: 4×3 and 3×4. 3×4 is chosen first, as $3/4$ is closer to 1 than $4/3$. $cond(1)$ is realized with bin_1: $3 \leq 8$ and $4 \leq 5$. Thus, $p_1 = \{1, 1, 3, 4\}$ (in grey). $Cond(2)$ is also satisfied: $3 < 8$. So a new bin, bin_2, is created: $bin_2 = \{4, 1, 5, 5\}$. Finally, bin_1 is updated:$\{1, 5, 3, 1\}$. This process is repeated for every information piece, and a layout, like the one shown in Fig. 5-(c), is obtained.

V. Experimental Results

This section introduces the experiments and the experimental results of the proposed method. The first part evaluates the precision and the utilization of a visualization. The second part discusses a real implementation and its survey evaluations on a movie directory. It took place at the Hong Kong University of Science and Technology (HKUST), in order to get potential users to test the AVDD. The last part is a showcase to demonstrate the effectiveness of the system under other condition, such as transportation. It was conducted at the Kowloon Motor Bus Company (KMB) headquarters, and the purpose was to evaluate the practicability and usefulness of the system in other conditions, and from the information providers side.

A. Utilization and Precision

Two metrics are used: the utilization, υ, and the precision, σ. The optimized visualization aims at achieving minimizing unused areas in a display without the harm about customizing information with high relevancy. So, the utilization shows how much of the display area, A, is used in Fig. 6-(a), and the precision compares the actual area composed of numbers of unit cells on a display allocated to an information piece with the ideal one optimized as shown in Fig. 6-(b) as follows:

$$\text{utilization} : \upsilon = \frac{\sum_{i=1}^{N} a'_i}{A}. \tag{12}$$

$$\text{precision} : \sigma = \frac{1}{N} \sum_{i=1}^{N} \frac{|a'_i - a_i|}{a_i}, \tag{13}$$

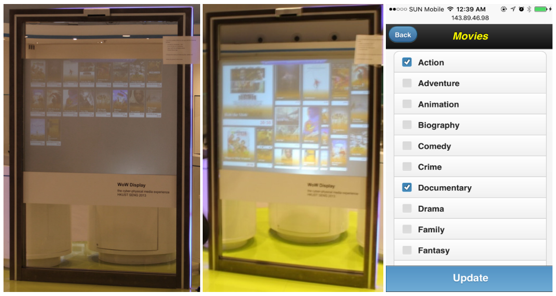
where a_i and a'_i are the optimized area and the area after placement of p_i. Two sets of scores are used to verify the framework efficiency, one from a uniform distribution and one from a Poisson distribution. The results for the utilization and the precision are converted into percentage and are described in Fig. 6-(c) for 5 different numbers of information pieces $N = \{10, 20, 30, 40, 50\}$ and 3 different numbers of cells $n = \{100 (10\times10\text{grid}), 200\ (20\times10\ \text{grid}), 400\ (20\times20\text{grid})\}$. The value of α and λ used for the score processing are chosen as previously defined. Also, μ is taken as equal to 1% of the display area. Each configuration is run 100 times.

As shown in Fig. 6, the precision σ is correlated to n (the total number of cells) and N (the set of information pieces). First, σ increases when n increases. However, n has to keep appropriately small as it defines the possible allocations C, a big n means the small size of the unit cell and thus results in many possible shapes available, making the visualization less easy to read. In addition, σ decreases when the number of N increases. But it is generally above 75% for common situations of a directory.

The utilization υ is always higher than 98% on average, so the display area is almost fully utilized for every scenario. As well, the precision σ is higher with relevance scores from a uniform distribution than from a Poisson distribution. This can be explained by the fact a Poisson distribution generates more heterogeneous cell allocations. Finally, such results demonstrate the good performance of this optimization framework to place information pieces, while conserving their ratio and fully utilizing the display area.

B. Quality of User Experience

A multimedia content directory with movie posters and descriptions is implemented and 18 movies are visualized on public displays at HKUST as a directory. Each movie is characterized by a title, a category, an opening time, and a poster. The directory is prepared with two visualization



(a) (b)

Fig. 7: Multimedia content visualization as directory: (a) legacy, (b) AVDD with user preference selection.

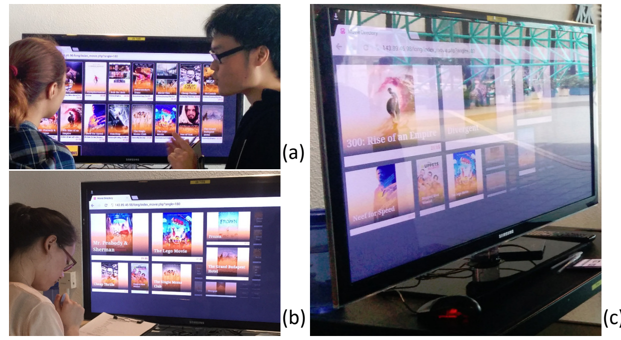


Fig. 8: Movie directory: (a) legacy, (b) random (b) AVDD.

strategies: 1) the legacy way with the same size of multimedia/text contents and sequential display and 2) customized view by the proposed framework. Users choose their movie preferences via their own smartphones. Fig. 7 shows such two methods to visualize a directory: (a): the legacy way and (b): user preferences selected by their own smartphone and AVDD for the customized visualization by such preferences. Namely, the multimedia directory is customized to give a bigger size to movies corresponding to their preferences. In following paragraphs, a real survey is conducted as evaluation for user experiences of this movie directory.

The system was firstly tested using the moveable TV display at HKUST, as shown in Fig. 8. It was located in a well-frequented area of the university that is known to be "Cafe" during two weekdays. The display showed a list of 18 movies. A board was used to attract people to the screen and to use the system, and phones were available for interacting with it. Totally, 30 people have participated in this experiments and their information and experiment setups are explain in the Table I. For this experiment, we prepared three scenarios to visualize the movie directory: 1) the legacy method, 2) discriminated display based on randomly selected preferences among movie type categories, 3) customized display with selected preferences of participants among movie type categories. The system was introduced to them, and then they can use the system freely. The participants selected their preferences by choosing the categories with their own phone. People who interacted with the system for 15 minutes on average were asked to fill in the questionnaire presented in Table II using the Likert scale [43]. They were asked to answer on a scale of five degrees, from "1: strongly disagree" to "5: strongly agree". The survey assessments are organized two types: positive questions and negative questions. For example, a question "I feel comfortable using this system" is positive; on the other hand, "Finding relevant movies is hard" is a negative one. In addition, the id 4, 5, 7, 9, 11, 12, and 13 are the general questions which can be answered for all the display scenarios (legacy, random, and AVDD) since the others are only related to random and AVDD which rely on smartphones and different sizes of contents. The final result is a score on a scale of 0 to 100. To provide better readability, the negative results are regulated to positive values as shown in Fig. 10. For example, the score "5: strongly agree" for a negative question is inverted to "1: strongly disagree" with a positive question, and vice versa.

Fig. 9 shows the average scores for each assessment for AVDD and random scenarios and only general questions for all scenarios. All the results support that AVDD provides better experiences to choose interested movies. Interestingly, for comparison between the legacy and random, the legacy shows better results than random such as the assessment 4 and 11. In addition, Fig. 10-(a) describes the total average scores 75.5 of AVDD for all the assessments which are calculated with inverted values of negative assessments. Namely, to get the total average of positive and negative assessments, negative assessment scores are inverted as positive scores that the highest score means "strongly agree". Fig. 10-(b)

Participants		
Sex	Male	Female
	16	14
Age	18-20 years old	20-30 years old
	7	23
How often	1 and more per a month	Less
	27	3
Experiment setup		
Visualization unit	Web-based system	Android dongle (HDMI + USB)
Analytics system	Windows 7 base	Apache+PHP+MySql
SSI interface	AndroidiOS phones	Web browser
Interaction	Javascript	WebSocket

TABLE I: Evaluation Information

ID	Assessment	Type
1	A smartphone is convenient to collect and send my preferences.	P
2	A smartphone is convenient to trigger the system.	P
3	It requires much effort to take the smartphone out of the pocket for interacting.	N
4	It requires much effort to learn to use this system.	N
5	I feel comfortable using this system.	P
6	The biggest movies are relevant to my interest.	P
7	Finding relevant movies is hard.	N
8	It is clear that the biggest movies are the more relevant.	P
9	The system fails to help me pick a movie to watch.	N
10	I am confused by the size of the movie when I choose.	N
11	I would like to use the system at a movie theater.	P
12	Overall I think the system is efficient.	P
13	Overall I like interacting with the system.	P

TABLE II: Likert assessments of experiments for user experience at movie directory. (P: Positive, N: Negative)

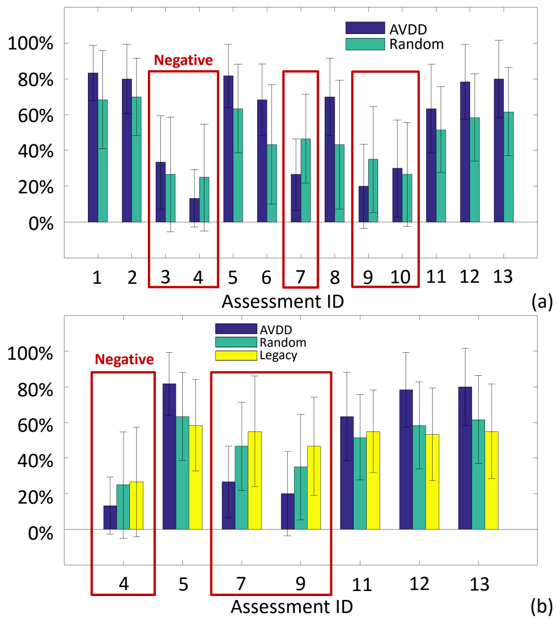


Fig. 9: Likert score from movie experiment: (a) scores of each assessment, (b) scores of each general assessment.

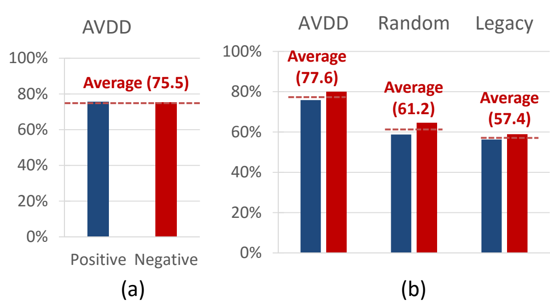


Fig. 10: Likert score from movie experiment: (a) scores of total assessments of AVDD, (b) scores of total general assessments. Note that the scores of negative questions are inverted.

illustrates the average scores of each visualization scenario merely for the general questions. The results are 57.4 for legacy, 61.2 for random, and 77.6 for AVDD. The conclusion from the scores are as follows: 1) proposed AVDD always has higher scores than random and legacy; 2) Random and legacy have similar scores, but for 4 and 11 legacy shows better values since the random could make smaller sizes of relevant movies. In addition, participants liked the use of a smartphone to interact with the AVDD and mainly agreed that it is a convenient device for such interactions. Then, they agreed that the customized visualization helps them to find relevant movies. The fact they can choose to customize the visualization by turning the phone to the display made them try to evaluate the contribution of each user. Finally, they deemed that the system is efficient to use and they were willing to use it at a movie theater.

C. Content Provider Perspective

Finding the right bus is a common task facilitated. An implementation was realized at KMB headquarters with real data, such as route number, destination and arrival were stored in the AVDD. In the experiment, 9 employees from KMB (6 males, 3 females) tested the system within two sessions (session 1 with 4 employees and session 2 with 5 employees). On average, these employees had been working at KMB for 14 years. Afterward, each group interacted with the system. Fig. 11-(a) shows the legacy visualization for a bus directory and Fig. 11-(b) shows an example of the customized visualization.

After interacting, they were asked to answer the questionnaire presented in Table III on a Likert scale. Fig. 12-(a) shows the average score by assessment, with a range of 51-80 (average 69.5). The system was deemed convenient to use. Participants mainly agreed that it is clear that the biggest information is the most relevant. Moreover, they had confidence in choosing the bus that was displayed bigger.

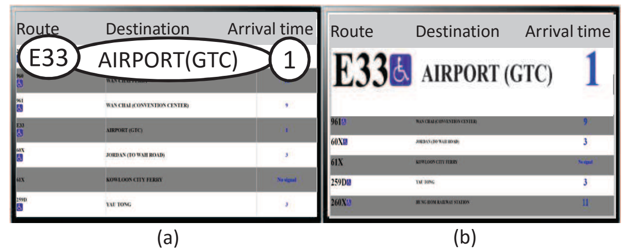


Fig. 11: Bus directory: (a) legacy, (b) AVDD.

ID	Assessment
1	The system solves a real problem.
2	The system is convenient and easy to use.
3	Using the phone to send preferences to the system is convenient.
4	It is clear that the biggest information is the most relevant.
5	The customized visualization makes me confident that I choose a good bus.
6	The group customized visualization makes them confident in choosing a good bus.
7	I am likely to interact with this system at a bus stop.
8	Such a system can be useful for bus operation.

TABLE III: Likert assessments of experiments for user experience at bus directory.

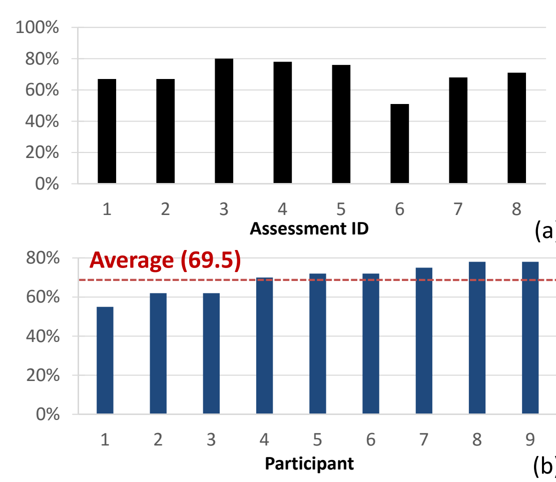


Fig. 12: Likert score from KMB experiment: (a) average score for each assessment, (b) score of each participant and average.

	Physical directory	Digital directory	Touchscreen directory	AVDD
Dynamic content update	✗	✓	✓	✓
Customized visualization (single user)	✗	✗	✓	✓
Customized visualization (multiple users)	✗	✗	✗	✓
Optimal display utilization	✗	✗	✗	✓

TABLE IV: Advantages of AVDD.

However, they thought that the system could be improved for multiple users. They also mentioned if the visualization change smoother, it will help them to locate the information. Finally, they agreed that such a system could be used at bus stops, especially when a large number of buses are available. Fig. 12-(b) shows the average score of each participant, with a range of 55-77.5 (average 69.5).

D. Discussion

The AVDD has been tested by information providers and users. First, the use of smartphones for interacting was appreciated by users. An unexpected effect was the fact that many users tried to not interact with the system simultaneously in order to evaluate everyone's contribution. However, some problems were encountered when using the orientation sensor, as different phone sensors may give significantly different orientation values. Then, giving a bigger size to relevant information can facilitate the search for information. By only updating the size and position of information whose relevance changes during the interactions can also help the information searching. Furthermore, though the relevant information was displayed bigger, people seemed not to worry about their privacy. Such a result can be explained by the fact that people interacted within a group and the content is not sensitive.

Calculating the relevance of a piece of information to a user is always important. That calculation could be based on information from social media, such as social graphs [34], and even user generated content such as images. On the other hand, with the use of wearable devices, more and more data is generated, such as heart rates and motion information. Further investigations are needed how to utilize those information, and make a better relevance to improve AVDD.

VI. Conclusion

This paper presented AVDD which provides novel customized digital directory services relying on screen-smart device interaction to: 1) exploit user information; 2) analyze relevancy between the user preferences and information content in a directory; and 3) fully utilize the screen area for optimized content visualization. AVDD was built and proved to fully employ the display area with utilization higher than 98% on average. The real implementations and surveys on visualizing informative data with an average score of 73% demonstrates its effectiveness. AVDD is the first attempt to advance directories with the key metrics on the evolution of directory technologies as summarized in Table IV.

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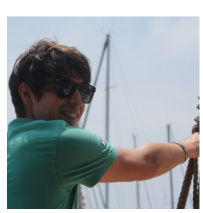

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