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Assessing personal screen exposure with ever-changing contexts using wearable cameras and computer vision

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A B S T R A C T

Electronic screens are ubiquitous in daily life and support everyday activities in different contexts. Moderate screen use is crucial to individuals' physical and mental health in modern society, while empirical research has verified the potential of altering psychology and behavioral choices by improving micro-environmental qualities. With the hypothesis that the ever-changing contexts may influence people's screen behavior, this article explores how design interventions in these micro-environments can promote healthier and more balanced screen use. To achieve this, the fundamental step is understanding how people utilize screens in diverse contexts, including indoor and outdoor spaces in free-living scenarios. Despite its importance, current literature offers limited methodologies for precisely examining screen behaviors and their contexts simultaneously. To address this gap, this study proposes an automated method with wearable cameras and Computer Vision technologies to quantify screen exposure and related daily contexts extracted from the collected life-logging images (N = 30,186). "Indoor" and "desk" are found to be positively associated with the occurrence of screen behavior. Conversely, "greenery," "crowd," "travel," and "food" exhibit robust and negative relationships with screen exposure. This study offers a new approach to objectively and automatically measure screen exposure, enhancing efficiency and reliability over conventional methods. Moreover, it establishes a replicable framework for future research on broader datasets and informs the fields of architectural and urban design on molding healthier and more balanced screen use among individuals.

1. Introduction

Exposure to digital screens has become ubiquitous in contemporary society [1,2]. Nevertheless, problematic screen use can lead to social-emotional delays [3], unsatisfactory academic performances [4,5], depression [6], dry eye syndrome [7], and potential risks that threaten road safety [8–11]. Therefore, moderate and regulated screen use is of great importance, as it affects many aspects of health, safety, and individual development. Furthermore, abundant studies have underscored that environmental factors play a significant role in shaping human experiences and behaviors [12–15], including screen behavior and its interrelated ones (e.g., sleep, health, work, sociality, etc.). For example, previous studies found that sleeping close to a small screen or having a TV in the bedroom, along with increased screen time, are associated with shorter sleep durations [16]; parental screen-viewing time, and access to electronic media (TVs, PCs, laptops, game equipment) in domestic settings are strongly associated with children's overall screen exposure time [17–19]; heightened consumption of sugar-sweetened beverages, fast food, and salty snacks due to higher levels of TV viewing and exposure to marketing of unhealthy foods raises obesity risk [20,21]; thermal environment, lighting conditions, and layouts are essential correlates with employees' reactions and performances in workplace, which is primarily involved with screen usage [22–25].

The contexts of screen behaviors, referring to the surrounding micro-environments of individuals, are dynamic and constantly changing, especially with technological advancements in screen sizes and features. The spectrum ranges from entertainment-driven activities in domestic settings to professional and educational pursuits in work settings, extending to information dissemination in transportation and outdoor environments. An investigation of how the contexts influence screen behaviors is necessary to foster sustainable environments and develop

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tailored environmental interventions to encourage balanced screen use in contemporary lifestyles. Previous explorations have included applying questionnaires [26–28] and screen time tracking apps [29–31] to gather screen time data; using wearable cameras and collected egocentric images to categorize and quantify the contexts (where, when, and with whom) of screen use in adolescents manually [32]. However, constrained by methodologies, existing literature has two main gaps: first, high-resolution spatial-temporal contexts of screen use are challenging to capture and incorporate, with characterization and categorization being generic and limited in diversity; second, measuring and combining screen time is time-consuming, particularly in scenarios involving multiple screens. With the hypothesis that ever-changing contexts may influence people's screen behavior, this study proposes a methodology that applies wearable cameras (Narrative Clip 2) and Computer Vision to automatically track screen behavior and its related contexts in free-living scenarios. It specifically investigates the effectiveness of the proposed methodology to examine the intertwined relationships between the everyday activity-based micro-environments (greenery, crowd, travel, indoor, food, desk) and screen behaviors, potentially expanding the scope and improving data granularity in related research areas, including sedentary and obesity studies, social performance literature, and indoor environmental quality literature. Its accuracy is cross-validated by comparing results with conventional approaches. Additionally, the proposed methodology has the potential to detect screen and content attentiveness with more sophisticated Computer Vision models and is replicable for larger datasets in future studies. Finally, this study enriches the literature by shedding light on environmental interventions that can effectively mitigate personal screen exposure time, providing invaluable insights for professionals across diverse domains, including human behaviors, public health, and architectural and urban design.

2. Related work

2.1. Important contexts interlocked with screen behaviors

Helbig et al. [33] have highlighted the need to examine personal environmental conditions to better understand individual behaviors. Screen usage often co-occurs with other activities such as eating, sleeping, sitting at work, and commuting. Studies have also shown that screen usage is closely related to green activities, outdoor activities, and offline social networking, which are crucial for overall well-being. Thus, it is essential to explore the relationship between screen use and contexts in these scenarios.

Although prior research has connected screen behavior to different settings, a clearer understanding of the direct links between the two is still needed. Furthermore, the current generic and singular way of describing contexts limits the depth of insights. Thomas et al. [32] classified screen use physical contexts into three main categories: "home," "public," and "transport," with further subdivisions such as "living room," "bedroom," and "kitchen." However, this approach fails to consider micro-environmental factors that may impact screen behavior on an object level, such as outdoor greenery, office desks, and food items. Other studies, such as those conducted by Jago et al. [17] and Sirard et al. [19], have examined more specific contexts, such as the number of televisions in a household and parental screen time, but these singular contexts cannot fully capture the complexity of screen use contexts.

Therefore, a holistic approach that considers diverse and specific contexts is necessary to investigate the impact of environments on screen behaviors, which is helpful in informing environmental interventions that promote moderate screen use.

2.1.1. Greenery context

A previous study shows that parents' restrictions for outdoor play were associated with higher children's TV viewing in domestic environments [34]. Screen time and green time have contrasting psychological outcomes on individuals [35]. Poor psychological conditions and stress may lead to addiction-related habits, including increased reliance on screens, which are associated with other emotional problems, further deteriorating one's mental health [36]. Numerous studies have demonstrated that time spent in nature and exposure to greenery, such as parks, gardens, and other green environments [37–42], can be beneficial in alleviating symptoms of anxiety and depression. Notably, recent research underscores the significance of green time to individuals' well-being and suggests in-depth research on the relationships between screen time and green time, for example, how digital technologies could promote outdoor activities and engagement with green [35, 41].

2.1.2. Crowd context

In this study, the term "crowd context" refers to whether an individual is alone or in the presence of others nearby, reflecting the individual's social situations. In the context of family dynamics, prior research has revealed associations between parental behavioral characteristics, particularly TV viewing, and children's overall screen time [17,34]. Additionally, existing literature suggests that increased TV viewing among adolescents is associated with lower attachment to both parents and peers [43]. In today's digital era, people rely heavily on social media and digital tools for social interactions, leading to a blurred boundary between online and offline. Previous reviews have underscored the importance of methodological improvements, including passive experience sampling, to better measure digital technology and social media use [44]. Understanding screen behaviors in the "crowd context" is paramount for gaining knowledge of screen usage patterns, social relationships, and psychological well-being.

2.1.3. Travel context

People actively use screens during commutes in automobiles for work, navigation, entertainment, and time killing [45,46] or are passively exposed to public screens along the driveway and in transport hubs in urban settings [47]. Previous studies also pointed out that distractions caused by screen exposure could threaten road safety while walking and driving [8–10,45,48]. The heavy integration of technology and screens in travel settings urges a close examination of screen behaviors in travel contexts to inform transportation planning and guidelines to encourage responsible screen use.

2.1.4. Food context

Abundant studies have linked sedentary behavior, particularly screen time, with weight change [36,49]. Exposure to food and drink advertising on screens also contributes to unhealthy dietary habits [20, 21]. Time spent on TV viewing and console games were found to have a negative correlation with eating self-regulatory score, which is directly associated with weight gain during the COVID-19 confinement period [49]. Using self-reported screen time and energy intake data, a previous study found that screen time is associated with higher intake of overall energy and sodium, and a lower intake of fiber, vegetables, and fruits, especially among overweighed children [50].

2.1.5. Desk context

Screen time and sedentary time are intrinsically linked, especially in workplaces and academic settings where desk-based work is prevalent [22,51]. Existing literature has found similarities between screen time reduction and sitting reduction strategies, such as ergonomic workstations that encourage standing or moving, and technology-based interventions, such as software that reminds users to take breaks [52]. Given the unfavorable outcomes on health [53] and work performances associated with work-related sedentary screen time, such as dry eye disease [54] and stress [55], it is crucial to scrutinize the correlation between screen exposure and proximity to desk-related contexts, which is helpful for targeted self-regulations and environmental interventions to safeguard health and improve overall work outcomes.

2.2. Conventional methods to assess screen time and screen behaviors

Most studies rely on self-reported data and participant estimates of their exposure to screens and contexts, such as interviews, questionnaires, and time dairies. Caregiver-reported questionnaires are widely used in studying screen behaviors of the young [26,56–58]. Among them, Klakk et al. [26] developed the SCREENS-Q questionnaire, which encompasses questions about environmental factors and screen time, such as screen media environment, early exposure, parental media use, parental perception of a child's media use, etc., to measure screen behaviors. Neighborhood social and physical environmental features (e.g., street connectivity, neighborhood safety, infrastructure, etc.), together with children's usage of screens, were collected through questionnaires and found to have robust associations [58]. Questionnaires are also adopted to measure screen time and its associations with health issues and self-management. For example, Lubans et al. [27] examined the association between adolescents' motivation to limit their screen time and their self-reported screen time; Maras et al. [28] adopted multiple questionnaires to synthetically explore the relationships between sedentary screen time and symptoms of depression and anxiety in a large community sample of Canadian youth.

Another commonly used approach to examine screen behaviors is utilizing screen tracking apps installed on mobile devices (such as the Screen Time app for iOS and the Digitox app for Android) or other digital gadgets. These apps allow for the automatic recording of screen time [29–31]. Using this method, Loid et al. [59] assessed the relationship between smartphone use and problematic smartphone use to gain insights into the impact of screen usage on individuals' well-being. Interestingly, a previous study also combined questionnaire and tracking app methods to investigate the factors influencing technology acceptance among iPhone users [60].

Questionnaires and screen time tracking apps are widely adopted, and studies using these methods have significantly contributed to the screen behavior literature. However, the ever-changing contexts discussed in **Section 2.1** have not received enough attention in the current literature, and with traditional methods, it is hard to precisely measure screen behavior and environmental factors simultaneously. Moreover, existing literature also indicates that people tend to over-report or under-report their screen time, making the questionnaire method prone to subjective assessments [29,61–63]. Considering multi-screen use scenarios, it is also challenging to use screen time tracking apps to collect concurrent screen time on separate devices and obtain accurate estimations of one's overall screen exposure. Individuals may be exposed to screens on devices that cannot be reclaimed or do not support tracking apps.

2.3. Potential breakthrough by integrating wearable cameras and computer vision

The fusion of sensors and advanced machine-learning technologies has revolutionized the study of individual behaviors, spanning health, daily activity, and interactions. For example, previous research detected individuals' home-based activities by deploying non-invasive state-change sensors on multiple home objects (e.g., fridge, microwave, toilet, etc.) and integrating activity recognition algorithms supported by context-aware experience sampling [64]. Fusing data from mobile and wearable sensors (wearable fitness trackers and smartphone GPS), Fritz et al. [65] detected residents' occupancy in bedrooms during sleep episodes for further estimations of ventilation rates. Donges et al. [66] used camera-based monitoring to examine occupants' behavior patterns in buildings, focusing on the interactions between occupants and building equipment to provide insights into energy efficiency. Camera footage was also examined to monitor occupants' behavior trajectories in office buildings [15], and wearable trackers and smartphones were utilized to investigate individuals' thermal comfort [24].

Wearable cameras, considered portable sensors, offer a viable means to passively monitor comprehensive individual activities and behavioral changes, including physical motions [67], diets [68,69], and exposure to environmental features (e.g. greenery, neighborhood physical disorder, etc.) ([70]; Z. [71]). By continuously taking life-logging [72] images (refer to photos or visual records captured through the practice of life-logging, which involves constantly documenting various aspects of one's daily life experiences), wearable cameras offer researchers rich imagery data to denote individuals' behavioral patterns. They record environmental and spatial-temporal data, with which the exposure of individuals is recorded, and individuals act as explorers of the environments [33].

The most challenging aspect of current screen behavior studies, which widely apply questionnaires and screen time tracking apps, is measuring screen behaviors and their contexts concurrently, objectively, and comprehensively. However, combining wearable cameras with Computer Vision has opened a promising avenue for addressing these gaps. Wearable cameras provide an objective and real-time record [73], free from the subjective influences of participants' memory or self-reports. Previously, many studies tested the feasibility of using wearable cameras to measure screen exposure time by manually annotating the presence of different screen types shown in the lifelogging images taken at a specific time interval [74–76]. Along this line, Thomas et al. [32] manually categorized not only the screen types and contents but also the locations (e.g., living room, bedroom, food retail, etc.), social settings, interactions (e.g., alone, co-viewing with others, etc.), and co-existing behavior (e.g., writing using a pen and paper, eating a snack, etc.) of screen use. Notably, by fusing wearable cameras with deep learning algorithms, Adate et al. [77] proposed a screen detection method by analyzing egocentric videos taken by wearable cameras to detect the presence of multiple kinds of digital screens (e.g., TV, smartphones, laptops, tablets, etc.) for screen-related longitudinal studies. Although these emerging methods have delved deeper into the nuanced patterns of screen behaviors, there is still limited knowledge of an automatic methodology to detect screen use and contextual information simultaneously, which could essentially save labor and time.

3. Data and methods

This study proposed a framework combining wearable cameras and Computer Vision technologies to improve the current methodology of assessing screen behavior and examining its associations with ever-changing contexts (Fig. 1).

3.1. Data collection using Narrative Clip 2

In May 2019, a group of volunteers encompassing a spectrum of lifestyles owing to diverse ages and professions (Table 1) was assembled utilizing social media platforms to incorporate a wide range of everyday life scenarios, thereby enhancing the robustness of the following analyses. The data collection was designed to obtain life-logging images of seven days of the five participants to record their activities from the beginning of each day until bedtime.

Narrative Clip 2 is a wearable camera chosen for this study. Its compact dimensions (36 x 36 $\times$ 9 mm), lightweight nature (19 g), soundless recording capability, high resolution (3264 $\times$ 2448 mm), and convenient clip-on attribute make it an optimal device for capturing daily life-logging images. A protocol was established to ensure participants recorded their images following consistent standards. Specifically, the cameras were set to capture images at a 30-s interval. Participants wore the Narrative Clip 2s on their collars, ensuring they were oriented forward, unobstructed, and sufficiently charged during the data collection. For privacy protection, participants were trained to turn off the cameras during activities or events deemed unsuitable for image capture, for example, at restrooms, banks, or hospitals. Additionally,

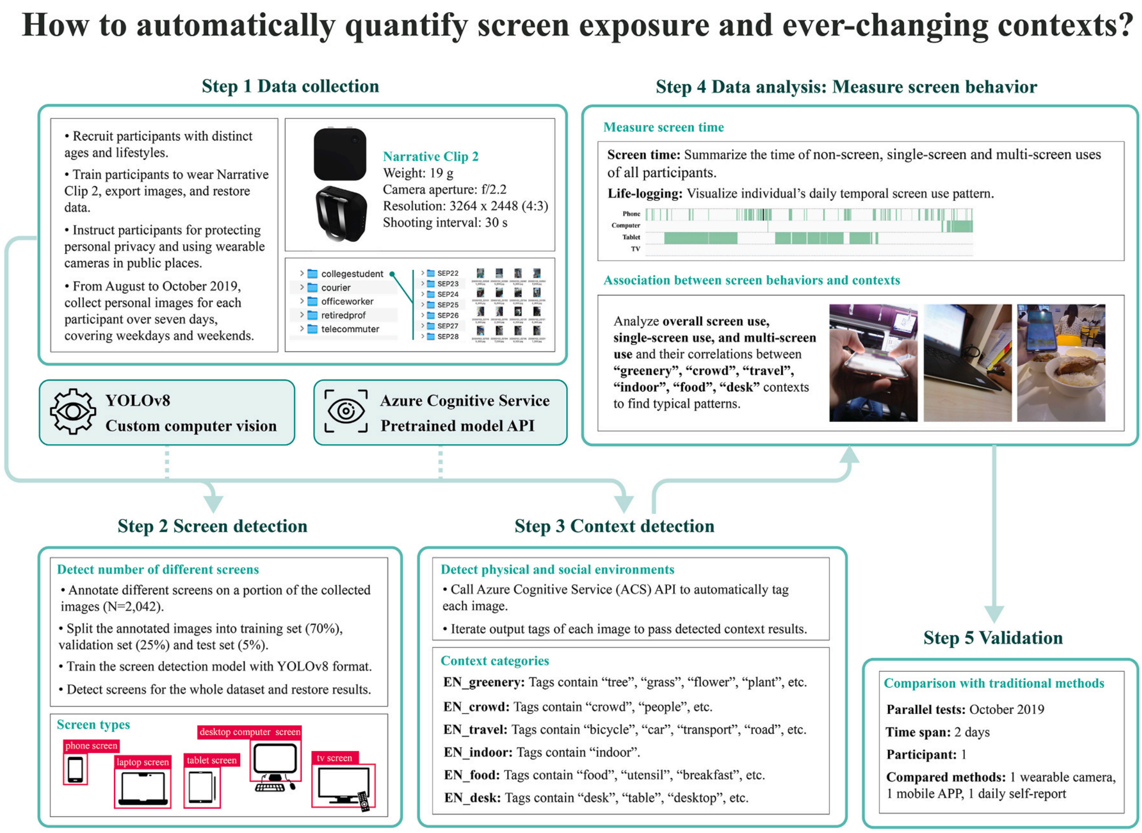


Fig. 1. Study framework.

participants were empowered to selectively eliminate images that did not align with their comfort level for sharing before submission.

Cumulatively, a comprehensive dataset of 30,661 personal images (equivalent to a total wearing time of 255.5 h) was acquired from participants, and a detailed data description is shown in Table 1. Data cleansings were facilitated by the Computer Vision API of Microsoft Azure Cognitive Service [78], which automatically applies tags that are based on a set of thousands of recognizable objects to the images, including tags such as "dark" and "blur." 1.55 % of the total dataset was identified as deficient in quality and lighting, and a final set of 30,186 valid images (98.45 %, translating to 251.6 h) was retained for the following analyses.

Notably, the quantity of daily life-logging images of Participant 2 (Telecommuter) is comparatively lower (N = 3988). This is primarily attributed to the participant's daily routine involving numerous privacy-concerned activities, particularly related to maternal and infant care, which were inconvenient for photographic documentation. The quantity of the last data collection day (Table 1, 29-Sep, 280) of Participant 2 was affected by the battery aging of the camera. Such an issue was also mentioned in previous research, which states that the battery lifetime of wearable camera devices decreases with the age of the camera [79] and should be noted for future studies.

3.2. Screen detection using YOLOv8

With the Ultralytics YOLOv8 framework ([80]: The State-of-the-Art YOLO Model), training screen detection models with a custom training dataset has become convenient. This study encompasses phone screens, laptop screens, tablet screens, TV screens, and desktop computer monitor screens, considering both portability and stationary screen usage. To enhance the model performance, supplementary data (N = 197) from the Roboflow Universe platform (users share open resource data to the Roboflow community, *Roboflow: Everything You Need to Build and Deploy Computer Vision Models*, n.d.) was included in addition to the randomly selected self-collected images from the five participants (N = 1845) to build the training set (N = 2042). A detailed breakdown and description of the training dataset are shown in Table 2. After the annotation process of all the selected images, which was conducted over Roboflow by the first author of this study, data augmentation (horizontal flipping) was applied to increase the dataset (N = 3082). The dataset was split into a training set (80 %), a validation set (13 %), and a test set (7 %), and the training process lasted for 30 epochs. The final trained model achieved a mean Average Precision (mAP50-95) of 84.5 % calculated over the Intersection over Union (IoU) thresholds ranging from 0.5 to 0.95. This comprehensively evaluates the model's performance across a spectrum of overlapping criteria, capturing how well it localizes objects with varying degrees of intersection with the ground truth. The mAP50-95 for different screens are phone screens (87.6 %), laptop screens (90.2 %), tablet screens (90.4 %), desktop computer screens (72.5 %), and TV screens (81.7 %), respectively.

3.3. Context detection using Microsoft Azure Cognitive Service

This study selected the essential contexts that are closely interlocked with screen behaviors as discussed in Section 2.1, "EN_greenery," "EN_crowd," "EN_travel," "EN_food," and "EN_desk," to test the associations between screen behaviors and micro-environments. "EN_indoor" was also selected to further differentiate indoor and outdoor settings, which may influence individual screen activities. The selected six contexts were further defined by keywords extracted from images using Microsoft Azure Cognitive Service. Previously, Zhang et al. [71] applied Microsoft Azure Cognitive Service to extract greenery tags to assess personal greenery exposure, demonstrating the feasibility of defining context with categorized keywords. In total, 859 keywords were extracted from the 30,186 valid images. The first author reviewed all the keywords and screened out related ones based on the context categories.

Table 1
Data descriptions.

ID	Occupation	Age				
1	College student	23	Date of year 2019	Total No. images	Valid No. images	Valid Percentage
			22-Sep	1175	1174	99.9 %
			23-Sep	1036	1031	99.5 %
			24-Sep	1267	1265	99.8 %
			25-Sep	824	824	100.00 %
			26-Sep	858	858	100.00 %
			27-Sep	894	892	99.78 %
			28-Sep	1042	1040	99.81 %
			Sum	7096	7084	99.83 %
2	Telecommuter	27	Date of year 2019	Total No. images	Valid No. images	Valid Percentage
			23-Sep	641	641	100.00 %
			24-Sep	632	632	100.00 %
			25-Sep	472	471	99.79 %
			26-Sep	622	622	100.00 %
			27-Sep	674	674	100.00 %
			28-Sep	667	667	100.00 %
			29-Sep	280	280	100.00 %
			Sum	3988	3987	99.97 %
3	Office worker	24	Date of year 2019	Total No. images	Valid No. images	Valid Percentage
			2-Aug	874	863	98.74 %
			8-Aug	870	847	97.36 %
			9-Aug	667	606	90.85 %
			10-Aug	1017	975	95.87 %
			16-Sep	1147	1136	99.04 %
			18-Sep	1178	1157	98.22 %
			19-Sep	1525	1461	95.80 %
			Sum	7278	7045	96.80 %
4	Retired professor	84	Date of year 2019	Total No. images	Valid No. images	Valid Percentage
			22-Sep	636	634	99.69 %
			23-Sep	1029	1020	99.13 %
			24-Sep	1004	995	99.10 %
			25-Sep	1188	1174	98.82 %
			26-Sep	1159	1155	99.65 %
			27-Sep	1049	1041	99.24 %
			28-Sep	887	870	98.08 %
			Sum	6952	6889	99.09 %
5	Delivery courier	32	Date of year 2019	Total No. images	Valid No. images	Valid Percentage
			24-Sep	813	802	98.65 %
			25-Sep	875	868	99.20 %
			26-Sep	797	780	97.87 %
			27-Sep	425	424	99.76 %
			28-Sep	610	609	99.84 %
			15-Oct	838	785	93.68 %
			16-Oct	989	913	92.32 %
			Sum	5347	5181	96.90 %

A complete list of keywords for each contextual category and corresponding meanings is presented in Table 3.

3.4. Combination of detection results

Screen and context detection results were saved with the unique file IDs for each image, making it possible to merge them by matching IDs. Fig. 2 demonstrates a sample image of each participant and the detected results. **TYPE** represents the screen use types, which encompasses non-screen use, single-screen use, and multi-screen use. **SCREEN** documents the detailed screen types for single-screen use and multiple-screen use. The detection of laptop and desktop computer screens are combined as computer screens for further detailed analysis. For example, in Fig. 2 (b), although the trained model detected the image to contain one laptop screen and one desktop computer screen, the result was simplified as a multi-screen use (TYPE) with computer + computer (SCREEN). For each image, the corresponding context of "EN_greenery," "EN_crowd," "EN_travel," "EN_indoor," "EN_food," and "EN_desk" was documented as positive (1) or negative (0), representing whether the context was detected.

3.5. Screen time measurement

This study examines the amount of time people are exposed to screens, including single-screen ("phone," "laptop," "tablet," "computer," "TV") and multi-screen use (combinations such as "phone + computer," "phone + tablet," "phone + TV," etc.) scenarios. Screen time is calculated by multiplying the total number of photos capturing occurrences of each screen use type by the photo-shooting interval (T = 30s). To illustrate daily screen usage patterns, a life-logging diagram is generated for each participant.

3.6. Association between screen behaviors and contexts

To understand the relationship between screen usage and real-life environments, this study utilized bivariate correlation analysis on the 30,186 moments captured by wearable cameras. The study examined overall screen usage, single-screen usage, and multi-screen usage in relation to six different contexts: "EN_greenery," "EN_crowd," "EN_travel," "EN_indoor," "EN_food," and "EN_desk." The aim is to uncover any consistent patterns or trends that may be present.

4. Results

4.1. Accumulated screen time and distribution by categories

For more than half of the time (160.6 h, 63.9 %) that the cameras were worn, participants were not exposed to any screens. Overall, single-screen exposure takes up 33.5 %, equaling 84.2 h. Furthermore, multi-screen exposure accounts for 2.7 % of the time, which is 6.7 h. Screen exposure time accounts for 36.1 % of the total time recorded. However, it is crucial to note that this method may also capture and calculate passive exposure to screens where screens were recorded but not actively engaged.

Table 2
Training dataset descriptions.

Data resources		Total No. selected images	No. images labeled for different kinds of screens					
			Phone screen	Laptop screen	Tablet screen	Desktop computer screen	TV screen	Total
Self-collected data	College student	810	434	96	326	0	11	867
	Telecommuter	191	129	83	0	0	27	239
	Office worker	239	31	139	10	72	2	254
	Retired professor	301	239	0	0	0	107	346
	Delivery courier	304	229	0	0	0	0	229
Roboflow Universe supplement		197	3	30	117	52	12	214
Total		2042	1065	348	453	124	159	2149

Table 3
Description of the keywords selected for each contextual category.

Contextual categories	References	Meanings	Keywords
Greenery	[34–42,44,47]	Keywords related to greenery or plants, implying participants' exposure to natural environments	flower, grass, plant, tree
Crowd	[17,34,43,44]	Keywords related to interpersonal interactions, or mere presence of other people in the backgrounds, implying participants' exposure to crowd and social environments, contrary to a solitude situation	adult, interaction, toddler, crowd, smile, boy, girl, glasses, woman, human face, man, people
Travel	[8–10,45–48]	Keywords related to outdoors, transportation, and automobiles, implying participants' involvement in travel-related activities and mobility contexts	helmet, truck, motorsport, driveway, turnstile, traffic sign, metro, suitcase, tricycle, minivan, bicycle pedal, compact car, transport hub, airport terminal, traffic light, cycle sport, limousine, motorbike, taxi, metro station, automotive tail & brake light, biking, steering wheel, pedestrian, personal luxury car, public transport, sport utility vehicle, road bicycle, walking, full-size car, rear-view mirror, automotive exterior, executive car, pedestrian crossing, automotive mirror, bicycles–equipment and supplies, city car, train station, subway, bicycle tire, crosswalk, bridge, highway, bicycle frame, luxury vehicle, curb, motor vehicle, automotive design, traffic, cycling, elevator, seat belt, trip, vehicle door, driving, vehicle registration plate, mid-size car, travel, luggage, car seat cover, car seat, street light, luggage and bags, family car, transport, bicycle wheel, sidewalk, bus, passenger, bike, bicycle, motorcycle, airplane, auto part, tire, train, road surface, airport, wheel, land vehicle, car, road, vehicle, street, car mirror
Indoor	[81,82]	Indicating that participants are in an indoor environment	indoor
Food	[20,21,36,49,50]	Keywords related to food, beverages, and utensils, implying participants' exposure to dietary environments	jiaozi, sauce, sweetness, xiaolongbao, baozi, diet food, broccoli, italian food, hot dry noodles, spaghetti, drinking, drinkware, coffee table, juice, junk food, seafood, fried food, pizza, beverage, tray, ice cream cone, dim sim, asian soups, xiaochi, local food, whole food, side dish, pantry, ice cream, dim sum, greengrocer, leaf vegetable, natural foods, mandu, mineral water, fork, donut, doughnut, cafeteria, dining, fish, fast food restaurant, chinese food, pastry, baked goods, breakfast, beer, pot, instant noodles, cook, kitchen appliance, fruit, dessert, salad, bar, buffet, food processing, chinese noodles, dinner, bakery, ramen, cookware and bakeware, fries, pan, apple, steamed rice, knife, culinary art, frozen food, jasmine rice, porridge, white rice, french fries, stew, vegetable, dairy, refrigerator, cooking, food court, food storage, eating, menu, pasta, convenience food, noodle, drink, supper, kitchen, lunch, soft drink, snack, cup, trade, spoon, kitchenware, serveware, rice, grocery store, soup, chopsticks, kitchen utensil, plate, dishware, mixing bowl, dish, fast food, restaurant, cuisine, meal, tableware, bowl, food, breakfast cereal, birthday cake, brunch
Desk	[22,51–55]	Keywords related to office furniture, supplies, sitting or working gestures, implying participants' close proximity to desk environments, and possible involvement in sitting positions	pencil, bookshelf, drawing, headlamp, workshop, stationery, auditorium, seminar, paper product, work, pen, bookcase, classroom, shelving, learning, lamp, worktable, paper, post-it note, notebook, library, conference room, office, office instrument, mouse, lap, calculator, computer mouse, handwriting, shelf, computer desk, book, typing, meeting, monitor, conference hall, tablet computer, whiteboard, computer keyboard, chair,

(*continued on next page*)

Table 3 (*continued*)

Contextual categories	References	Meanings	Keywords
			personal computer hardware, computer component, desk, keyboard, netbook, computer hardware, office supplies, table, personal computer, office equipment, public library

According to Fig. 3(b), the most frequently appeared single-screen types are phones (44.7 h, 53.1 %), computers (28.9 h, 34.7 %), and tablets (6.1 h, 7.3 %), followed by TVs (4.15 h, 4.9 %). As shown in Fig. 3 (c), the top three most common combinations of multi-screen use types are “Phone + computer (196 min, 48.7 %), “Phone + tablet” (80.5 min, 20.0 %), “Phone + TV” (71 min, 17.6 %). This underscores the apparent tendency for people to engage in mobile-centric multi-screen use.

4.2. Individual participant’s screen exposure time and patterns

4.2.1. Single screen exposure

As shown in Fig. 4, The delivery courier and the retired professor share a similar screen use pattern by relying heavily on phones during daily activities. In contrast, the telecommuter and the office worker prominently employed computers for professional tasks, alongside substantial phone screen exposure. Among the five participants, the college student’s screen time distribution is notably balanced, encompassing phones, computer screens, and tablet screens, with a minor degree of exposure to TV screens.

Fig. 5(a) illustrates the total single-screen exposure time of the five participants, with a horizontal comparison conducted for each screen type. The delivery courier accounts for the most extended duration of phone screen exposure (845 min). The phone screen exposure of the 83-year-old retired professor, totaling 809.5 min, is closely followed. Interestingly, the highest duration of TV screen exposure also belongs to the retired professor (182.5 min); Among the participants, the office worker surpasses others with a substantial 1250 min of computer screen exposure, while the college student leads in tablet screen exposure, clocking in at 329 min.

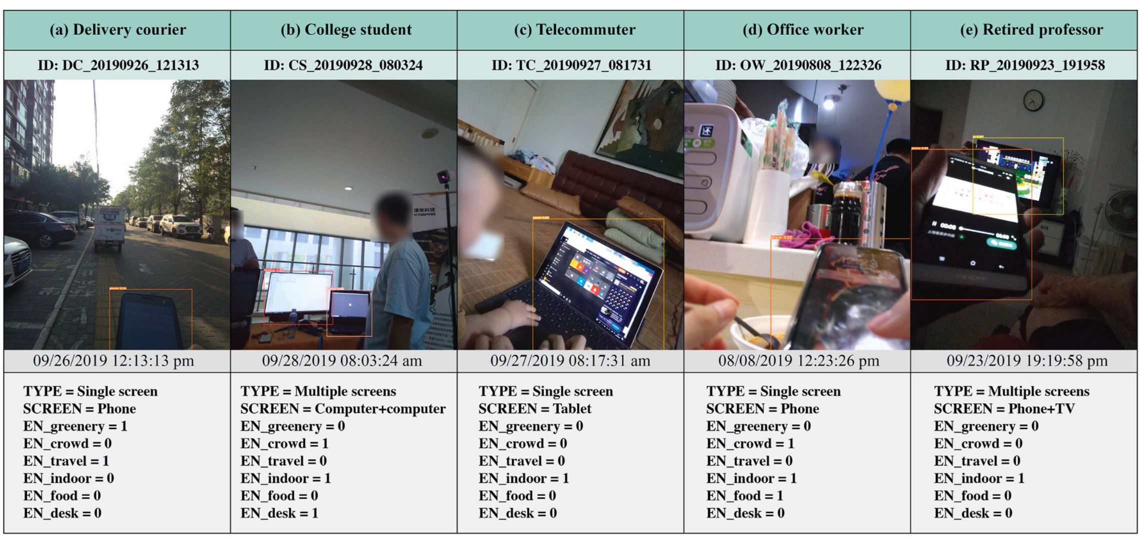
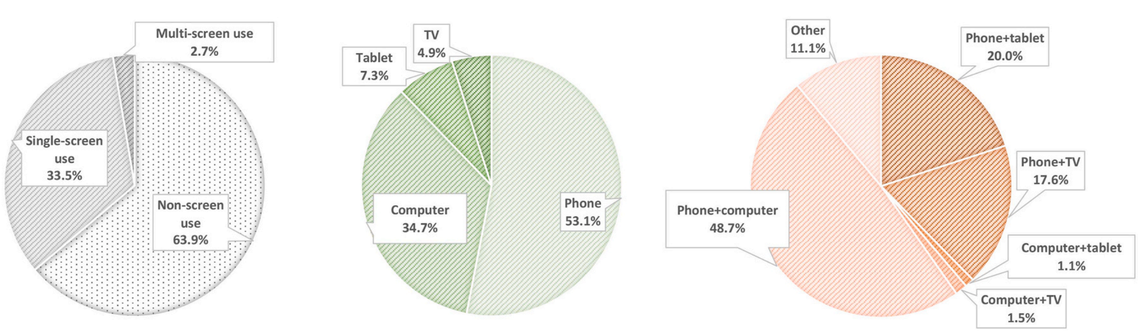


Fig. 2. Sample of combined detection results for each participant.
Note: “TYPE” refers to the screen use categories and encompasses “non-screen,” “single screen,” and “multiple screens”; “SCREEN” refers to the detailed screen types, which could be “phone,” “tablet,” “computer,” “computer + computer,” and “phone + TV,” etc. The “+” sign connects the concurrent use of different screens. “EN_greenery,” “EN_crowd,” “EN_travel,” “EN_indoor,” “EN_food,” and “EN_desk” refer to the context detection results for greenery, crowd, travel, indoor, food, and desk features, respectively. The detection result is binary for all the context types, where “1” represents positive and “0” means negative. The human faces in images are blurred for privacy considerations.



(a) Screen use types of all valid data. **(b) Single-screen use types.** **(c) Multi-screen use types.**

Fig. 3. Screen time distribution of all valid data (N = 30,186).

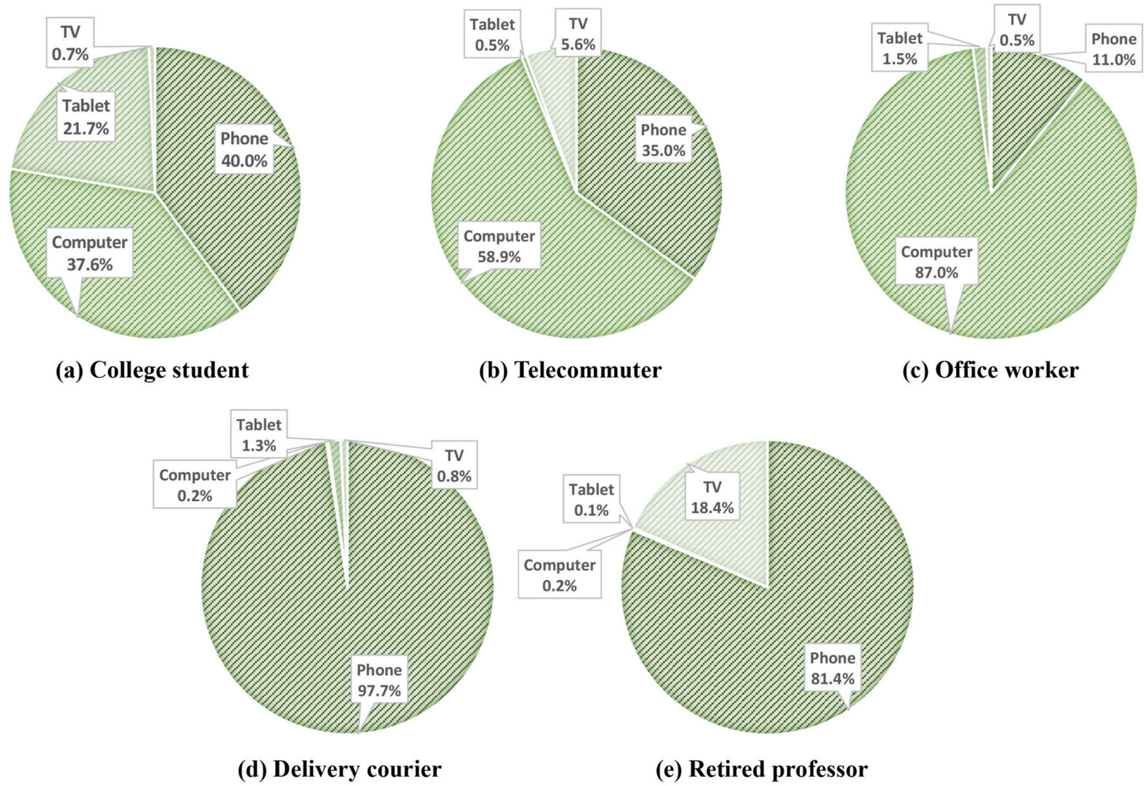


Fig. 4. Single-screen time distribution of five participants.

4.2.2. Multi-screen exposure

Evident from Fig. 5(b), the college student stands as the principal contributor to the duration of "phone + computer," "phone + tablet," and "tablet + computer" multi-screen exposure. Upon review of the college student's images, a recurring pattern of such combination screen uses was identified, frequently transpiring during academic-related activities, such as concentrated study sessions at the library or productive endeavors for curriculum projects at dormitories. Similar to the telecommuter, prolonged exposure to phone and computer screens was detected for professional work purposes. The telecommuter captured an accumulation of 4.5 min for concurrent exposure to computer and TV screens, and the personal images also imply the participant was working with the television turned on as a background. The simultaneous exposure time to both phone and TV screens is mainly contributed by the retired professor (69.5 min). The personal images show that the retired professor often uses the phone while indulging in nocturnal TV programming, thereby embracing this concurrent screen use for entertainment. Lastly, the delivery courier used multiple screens of the same kind for 33 min. The personal images show that it was common for the delivery courier to use several phones simultaneously to tackle mail delivery tasks.

4.3. The individual's time profile captured by the automatic framework

Compared with conventional approaches, the methodology employed in this study offers a more comprehensive means of capturing various aspects of screen usage, including instances of non-screen use, single-screen use, and multi-screen activities within different contextual settings. This is visually demonstrated in Fig. 6, where the participants' exposure to screens is depicted in both indoor and outdoor scenarios. Furthermore, it is also feasible to encapsulate discrete time intervals by accounting for the intermittent appearances of a specific screen type within the sequential array of an individual's daily lifelogging images, thereby treating these instances as distinct episodes of screen usage. For instance, the delivery courier was observed using the mobile phone up to 23 times within a single hour, with each instance averaging less than 3 min. However, these instances of brief screen time tend to be unintentionally disregarded in traditional research methods due to their fleeting nature and the limitations of personal cognition and recall.

4.4. The everyday contexts that are significantly associated with screen behaviors

By looking into the distribution of non-screen use, single-screen use, and multi-screen use in different contexts, we found that EN_desk and EN_indoor tend to have a more significant proportion of both single-screen use and multi-screen use compared with the other contexts. Fig. 6 highlights that exterior exposure usually occurs during screen use breaks, and prolonged screen usage and multi-screen exposure are predominantly observed indoors. We conducted a Spearman bivariate correlation test to further investigate the relationship between screen use behaviors and the ever-changing contexts. Table 4 concludes the test results, where EN_greenery, EN_travel, EN_crowd, and EN_food are found to be significantly and negatively correlated with all three types of screen use behaviors, while EN_indoor and EN_desk are found to have a robust positive correlation with screen uses. **Appendix 1** demonstrates various types of single-screen exposures and their duration distributions across six contexts.

5. Validation

5.1. Validation design

Questionnaires are convenient for collecting participants' perceived multi-screen time during the day, although they rely on subjective evaluations and recollections. On the other hand, screen time tracking apps excel in their objectivity. However, they are not available for all devices. Considering the merits and limitations of the traditional

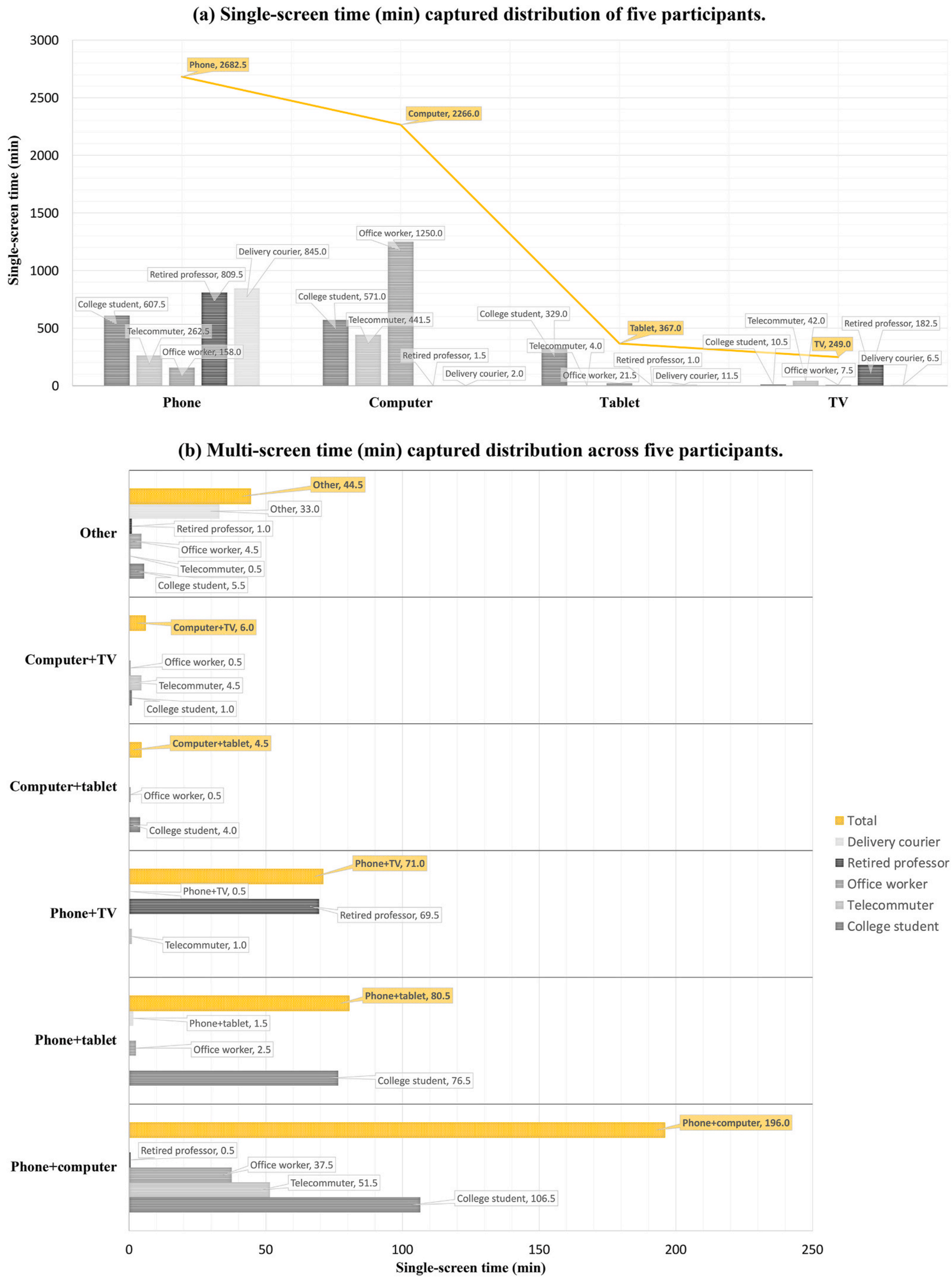


Fig. 5. Screen exposure time of five participants.

methods, the validation test employed a cross-validation approach to compare the results of the proposed method with both the questionnaire and the screen time tracking app methods.

The research team invited one of the five participants to participate in the validation test, whose tasks encompass the following: 1) wearing the wearable camera for an additional two days, 2) utilizing the Screen Time Assistant application (available on Android) on the mobile phone to log screen time during the same timeframe, and 3) filling in a questionnaire to report screen time based on recollections at the end of both days. For single-screen use, the questionnaire asked for the participant's daily exposure time ranges, which are "none," "less than 1 h," "1–2 h," "3–4 h," and "above 5 h," respectively. For multi-screen use, the questionnaire asked, "Which combination of multiple devices occurs more often?" A detailed description of the three sections of the validation process is shown in Table 5.

5.2. Validation results

- **Section A:** On day 1, the phone screen time measured by the proposed method aligned with 83.7 % (calculation: 79.5/95 = 0.837) of that recorded by the screen time tracking app, while on day 2, it was 69.3 % (calculation: 39.5/57 = 0.693) (Fig. 7(a)). Overall, the results measured by the wearable camera method closely matched 78.3 % (calculation: (79.5 + 39.5)/(95 + 57) = 0.783) of the time recorded by the screen time tracking app. The proposed method tends to underestimate screen time compared to the other two methods. This

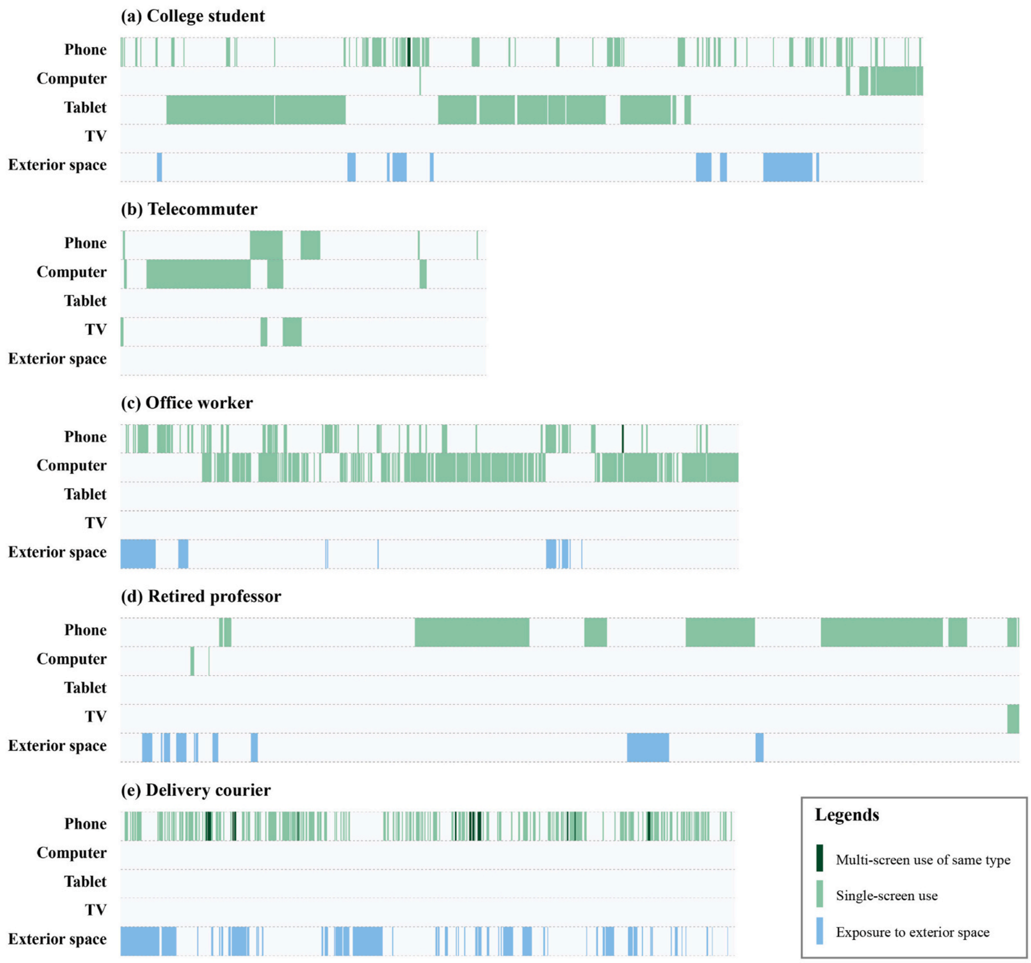


Fig. 6. Sample daily time slide profile of individual's temporal screen use patterns and exposure to exterior space (EN_indoor = 0).

stems from two main reasons. Firstly, it can only identify screens that are captured by camera frames. Thus, if screens are in use but positioned outside the camera's field of view, those instances of screen exposure would be missed. Secondly, there are instances where screens may go undetected by the trained model due to factors such as object occlusion and limitations in model accuracy. For day 2, however, neither the screen time measured by the proposed method nor the screen time tracking app fell into the time range (1–2 h) estimated by the participant.

- **Section B:** For both days, the computer screen time measured by the proposed method fell into the estimated screen time range (above 5 h) acquired by the questionnaires (Fig. 7(b)).
- **Section C:** According to the proposed method, the frequency of "computer + computer" occurrences is higher than "phone + computer" occurrences for both days. This is consistent with the questionnaire result obtained on Day 2. However, it contradicts the result obtained on Day 1, where the participant claimed that "phone + computer" was more frequent (Fig. 7(c)).

6. Discussion

6.1. Academic contributions

Addressing limitations in conventional screen exposure measurements, this study emphasizes incorporating the rich behavioral contexts extracted from high-resolution imagery data, providing a fresh perspective to observe and analyze screen behaviors. The application of Microsoft Azure Cognitive Service and the self-trained screen detection model drastically reduced the time and labor demanded by previous studies [32,74,76]. The methodology's effectiveness in measuring screen time is validated through comparisons with traditional approaches. Moreover, the robust correlations between screen exposure and various contexts (greenery, travel, crowd, indoor, and food) support the transfer and application of this method to related research areas. This is the first attempt to adopt wearable cameras and Computer Vision to quantify the associations between screen exposure and behavioral contexts automatically. Therefore, we primarily focus on constructing a theoretical framework and methodology refinements.

The proposed methodology surpasses the conventional methods in various aspects. First, it overcomes the limitations of the questionnaire method, which often suffers from issues related to participants' fuzzy memories and subjective responses. Utilizing wearable cameras to passively record life-logging images and extracting information with the assistance of Computer Vision makes the proposed method a more convenient, and reliable option with considerable objectivity than the conventional methods. Second, the proposed approach comprehensively captures multi-screen use scenarios compared to other logging methods (e.g., smartphone time-tracking apps and browser extensions). By setting personal cameras to take periodic shots, it eliminates redundant recordings across different devices. It enables the examination of screen exposure levels (including non-screen, single-screen, and multi-screen activities) throughout the day, especially when applying a larger dataset intended for a specific group of people for longitudinal studies. Third, the methodology excels in its ability to not only compare the accumulated time spent in screen-based activities and exposure to diverse contexts along the timeline but also to horizontally evaluate the

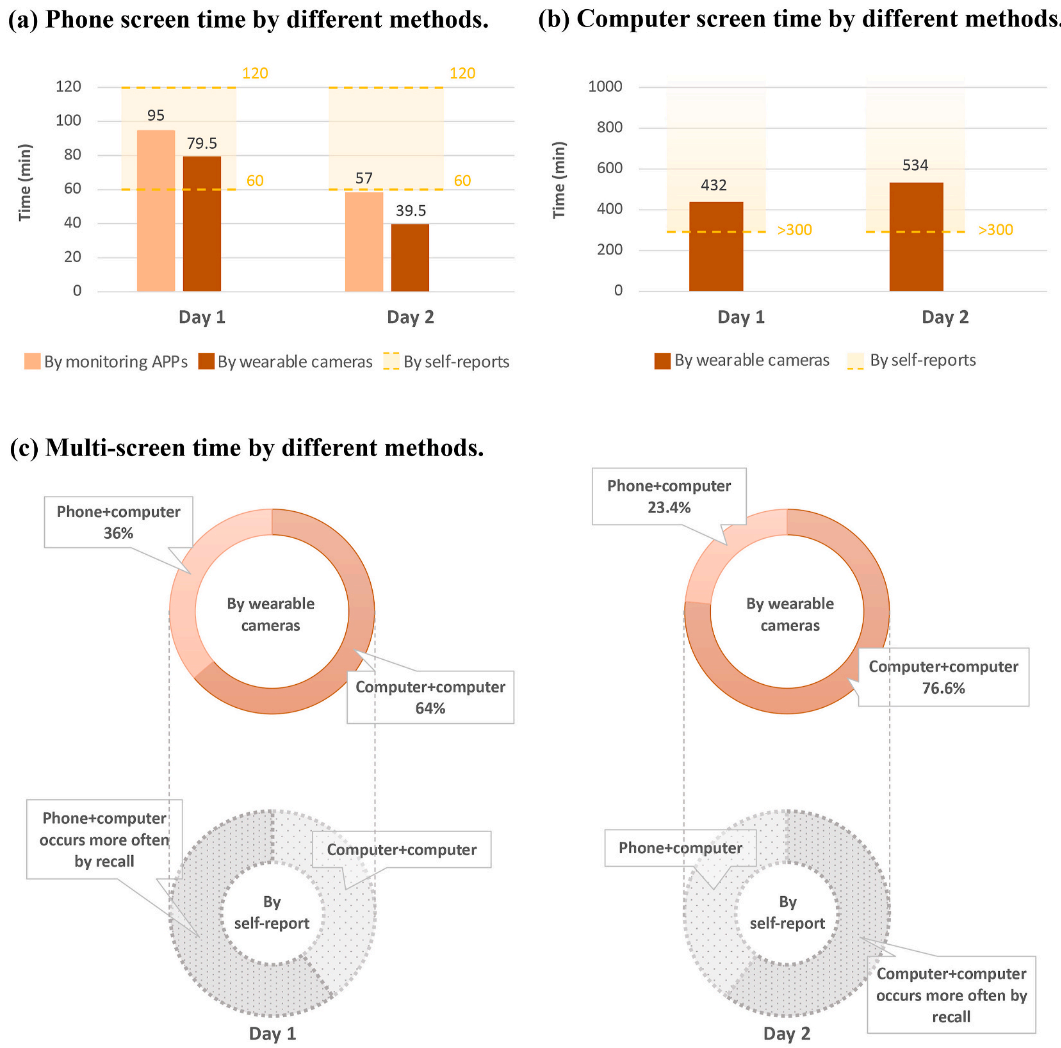


Fig. 7. Screen time by different methods: (a) phone screen time, (b) computer screen time, (c) multi-screen time.

Table 4
Spearman bivariate correlation coefficients.

	Screen use		Single-screen use		Multi-screen use	
	Corr.	Sig.	Corr.	Sig.	Corr.	Sig.
EN_greenery	−0.171	***	−0.155	***	−0.056	***
EN_travel	−0.174	***	−0.153	***	−0.071	***
EN_crowd	−0.167	***	−0.151	***	−0.056	***
EN_indoor	0.196	***	0.174	***	0.074	***
EN_food	−0.183	***	−0.169	***	−0.050	***
EN_desk	0.313	***	0.281	***	0.111	***

** Correlation is significant at the 0.01 level (2-tailed).

Table 5
Validation process description.

Section	Screen type	Screen use type	Methods compared with the proposed method	Time (days)	Participants (No.)
A	Phone	Single-screen	Questionnaire, screen time tracking app	2	1
B	Computer	Single-screen	Questionnaire	2	1
C	Phone + computer, Computer + computer, etc.	Multi-screen	Questionnaire	2	1

synchronization between screen use and occurrences of different settings.

6.2. Potential enrichment to behavior-related research areas

This innovative methodology also opens avenues for more comprehensive and insightful research in the dynamic landscape of behavior-related research areas. For example, examining screen exposure within the food and desk context and observing individuals' weight changes over time holds the potential to validate the reduced energy intake hypothesis in sedentary behavior and obesity literature, which links screen time reduction to obesity mitigation due to its correlation with decreased energy intake [83,84]. Existing literature identifies a concurrent tendency of increased screen time and decreased green time in younger generations in recent decades [35]. By measuring accumulated indoor and outdoor green exposure and overall screen exposure with the proposed method, researchers can precisely examine how individuals balance their time spent in nature and screen usage, and their implications on psychological and health outcomes (J. Zhang et al., 2023). Furthermore, the high temporal resolution of the proposed method paves the way for time-sensitive screen behavior research. For instance, as depicted in Fig. 6 (a), it is evident that there is a significant concentration of computer screen usage around the time when the college student sample day concludes. Logging and calculating the proportion of screen exposure at night in longitudinal observations could increase the data granularity for exploring bedtime screen use and its impact on sleep patterns and qualities [16,85,86].

In considering environmental factors, such as thermal comfort, office layout, and mechanical ventilation, as crucial elements in work settings [54,81,82,87,88], integrating wearable cameras with environmental sensors (for measuring temperature, humidity, air quality, etc.) [24] provides an opportunity to examine how indoor environmental quality influences individuals' screen usage and productivity. Moreover, combining wearable cameras with fixed cameras or occupancy sensors [15] paves the way to explore the potential influences of screen exposure on individuals' behavioral adaptions and interactions with indoor service systems (e.g., ventilation, air conditioning, etc.) [12,13], ultimately impacting building performance [65,66].

6.3. Designing environments for balanced screen use

The correlation results (Table 4) imply that people who spend less time on screens are more likely to spend time with access to greenery, attachment to other people, and dietary and travel activities. In contrast, prolonged time spent indoors and in proximity to desk environments is more likely to increase screen usage. Based on the robust associations between micro-environments and screen behaviors, suggestions regarding future interior and environmental design could be established to facilitate more balanced screen use in modern societies. Future studies could focus on the causal effects of environmental characteristics on screen behaviors to provide more in-depth and targeted design guidance.

6.3.1. Integration of green spaces and encouragement of outdoor activities

Architectural designers could consider integrating biophilic design [39] into interior spaces, including plants, living walls, natural materials such as wood and stone, and natural lighting to create more visually appealing and calming environments that reduce the reliance on screens [35,37]. Communities with pedestrian-friendly pathways [89,90], bike lanes, and accessible facilities could also promote outdoor recreational activities such as walking, jogging, and biking. Providing amenities such as outdoor spaces, rooftop gardens, or indoor green areas can encourage employees and students to take breaks and spend time in nature and outdoors (Z. [71]), thus reducing the possibility of excessive screen usage.

6.3.2. Creation of social interaction zones

Urban and architectural designers should prioritize the creation of outdoor public spaces and indoor communal spaces that encourage people to connect with the physical realms and their surroundings [43]. Parks, plazas, and cultural spaces can serve as hubs for in-person interactions and community events. Moreover, designating specific areas within architectural spaces, such as shared dining areas or open collaboration zones, can also encourage face-to-face engagements [91, 92] and reduce screen use.

6.3.3. Flexible workspaces

Create work environments that offer flexibility to accommodate diverse work styles. Incorporate features such as standing desks, flexible seating arrangements, and designated break areas to reduce prolonged screen time. Ergonomic considerations, including adjustable furniture [18,52] and lighting [23], could also contribute to a comfortable work setting and help ameliorate screen usage.

6.4. Limitations

Despite the advantages mentioned above, this method still holds some limitations.

- Similar to other logging methods (e.g., smartphone apps, browser extensions), it is still challenging to recognize screen attentiveness and focus, especially to distinguish which screen is more engaged by individuals in multi-screen exposure scenarios.
- Due to Narrative Clip 2's limited availability and high cost, collecting long-term and extensive data across multiple participants was challenging. We utilized data from only five participants over seven days for the correlation analysis.
- For the validation process, the sample size is limited ($N = 1$ participant, $T = 2$ days). Although we tried to enlarge the dataset, we were constrained by limited time and manpower to monitor participants conducting three parallel tasks (wearing wearable cameras and ensuring proper shooting, sending back screenshots of screen time app reports, and filling out and sending back questionnaires) every day. Additionally, not all participants frequently used computer and phone screens to ensure comparable screen time data to be collected, which also narrowed our options for participants in the validation process.

In Fig. 7(a) and **(c)**, we noticed discrepancies between the results obtained by the conventional methods and the proposed one. However, due to the limited availability and granularity of the validation dataset, we could not conduct a comprehensive comparison of the accuracy of the three methods. Specifically, we were unable to find an appropriate software that could be installed on the participant's computer to objectively measure computer screen time and multi-screen time in validation sections B and C. Moreover, the screen time ranges we set and how we acquired the multi-screen time in the questionnaire led to coarser screen time data compared with the ones obtained by the objective methods (the screen time tracking app and the proposed method).

- The non-random data loss caused by privacy concerns and battery depletion is a potential issue that requires attention in the wearable camera methodology.

6.5. Potential future enhancements of the methodology

Future research can apply the following strategies to enhance the method to address the above limitations.

- Detect screen attentiveness

Wearable camera models with wider-angle lenses and shorter capture intervals (e.g., iON SnapCam, GoPro) could be applied to enhance the inclusion of surrounding contexts. Future research can also focus on developing more sophisticated Computer Vision models to detect the frequency of variations in screen contents and brightness to predict individuals' screen attentiveness.

- Enlarge sample sizes and refinement of the validation process

Recruit a more extensive and specific group of participants (e.g., office professionals, elderly individuals) and observe screen behaviors for an extensive timeframe to collect larger datasets and acquire more empirical evidence to support the analyses. Furthermore, a broader range (e.g., more days and more participants) of datasets, granular time ranges in the questionnaire (e.g., 30-min intervals instead of 1-h intervals), a more comprehensive coverage of multi-screen use cases (e.g., add more screen types such as tablet to encompass diverse multi-screen scenarios), and comparative objective measures of screen time (e.g., app-based estimates of computer and tablet screen time) should be incorporated to strengthen the validation.

•Enhance documentation and monitoring of the experimental process

Request participants to record the number of manually deleted photos and the duration of non-capture each day, using a recall log to provide evidence for more precise subsequent analyses. Employ newly acquired devices to mitigate potential battery aging issues, and devices should be replaced promptly with regular monitoring of the camera's performance. Moreover, for future experiments, privacy protection for the public can be enhanced through more rigorous pre-experiment training.

7. Conclusions

In conclusion, this study introduces a pioneering methodology for measuring screen behaviors in free-living scenarios, leveraging the technologies of wearable cameras and Computer Vision. It not only significantly reduces the time and labor required by traditional methods but also ensures an objective and accurate assessment of screen time, especially in multi-screen use scenarios. The integration of detailed behavioral contexts, further defined by tags extracted from the images, facilitates a closer examination of screen behaviors. The robust associations between the various contexts and screen usage inform spatial interventions by future architectural and environmental design, including enhancing natural elements, creating outdoor spaces, designing flexible layouts and adjustable furniture, and promoting public and communal spaces. This study also provides a foundation for advancing research in various related areas, including sedentary behavior, obesity, green time, sleep patterns, work performance, and environmental psychology. The potential applications of the methodology extend beyond the study's scope, offering opportunities for interdisciplinary research and a deeper understanding of the intricate relationships between individuals and their surrounding environments. Despite the advancements mentioned above, this methodology also holds limitations, such as challenges in recognizing content and screen attentiveness, data loss out of battery and privacy issues, and limited data size. However, the study offers potential strategies to address these challenges in future refinements. This research not only inspires researchers, practitioners, and policymakers in fields such as public health, architecture, urban planning, and technology but also encourages further in-depth investigations tailored to specific demographic groups using the replicable methodology. To contribute to the academic community, the research team aims to share the annotated dataset and trained screen detection model, supporting future studies on broader datasets. By embracing the proposed methodology and its implications, stakeholders can actively contribute to creating healthier, more balanced environments that accommodate the evolving dynamics of screen usage in contemporary society.

CRediT authorship contribution statement

Nanxi Su: Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization, Writing – review & editing. **Zhaoxi Zhang:** Writing – review & editing, Software, Conceptualization. **Jingjia Chen:** Writing – original draft, Validation, Data curation. **Wenyue Li:** Conceptualization. **Ying Long:** Supervision, Methodology, Funding acquisition, Conceptualization, Writing – review & editing.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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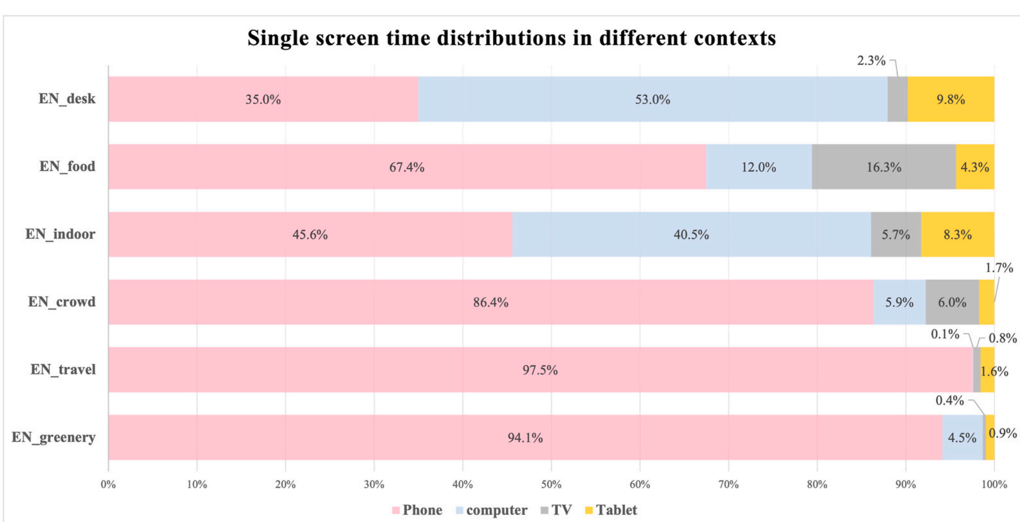
Appendix 1. Single screen time distributions in different contexts



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