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RESEARCH METHODS

Feasibility of Automated Cameras to Measure Screen Use in Adolescents

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Introduction: The influence of screens and technology on adolescent well-being is controversial and there is a need to improve methods to measure these behaviors. This study examines the feasibility and acceptability of using automated wearable cameras to measure evening screen use in adolescents.

Methods: A convenience sample of adolescents (aged 13−17 years, n=15) wore an automated camera for 3 evenings from 5:00PM to bedtime. The camera (Brinno TLC120) captured an image every 15 seconds. Fieldwork was completed between October and December 2017, and data analyzed in 2018. Feasibility was examined by quality of the captured images, wear time, and whether images could be coded in relation to contextual factors (e.g., type of screen and where screen use occurred). Acceptability was examined by participant compliance to the protocol and from an exit interview.

Results: Data from 39 evenings were analyzed (41,734 images), with a median of 268 minutes per evening. The camera was worn for 78% of the evening on Day 1, declining to 51% on Day 3. Nearly half of the images contained a screen in active use (46%), most commonly phones (13.7%), TV (12.6%), and laptops (8.2%). Multiple screen use was evident in 5% of images. Within the exit interview, participants raised no major concerns about wearing the camera, and data loss because of deletions or privacy concerns was minimal (mean, 14 minutes, 6%).

Conclusions: Automated cameras offer a feasible, acceptable method of measuring prebedtime screen behavior, including environmental context and aspects of media multitasking in adolescents.
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INTRODUCTION

Electronic devices, such as tablets, computers, and mobile phones, are common aspects of modern living. However, there is a concern that excess recreational use of these devices by children and adolescents is detrimental across a range of health and development outcomes,[1] including mental health, sleep,[2] and obesity.[3] Others have argued the effect of screen use on well-being may be negligible.[4] To better understand the influence of screen use on child and adolescent outcomes, it is important to have robust methods of measuring screen use.

Measuring screen use in adolescents is challenging. Researchers typically use self-reported questionnaires and diaries or activity logs to measure screen use[5] but these are unlikely to keep pace with the speed of technologic advances in product availability and usage. Screen use in children is often measured using parental reports, and there is evidence these are inaccurate for TV viewing in bedrooms.[6]

Mobile phones and other portable devices can be used frequently for short (sending a message) or long (watching a movie) bursts and often at the same time as doing other activities. This “media multitasking” is an area of growing interest, and adolescents and young adults are

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more likely to multitask than other age groups.[7] Research has focused on the negative effects of multitasking on learning and cognitive function in adolescents,[8] but multitasking may also negatively impact sleep beyond normal screen use.[9,10]

Automated wearable cameras have the potential to capture multiple lifestyle behaviors and the environmental context of these behaviors (e.g., use of devices while traveling) with little respondent burden. Such cameras have been used to explore a range of health-related behaviors and exposures, including sedentary behavior in young[11] and older adults,[12] physical activity in older adults,[13] diet in adults[14,15] and children,[16] food purchasing in adolescents while commuting,[17] and exposure to advertising in children.[18−20]

Given the importance of improving methods to measure complex screen behaviors, the aims of this study are to examine the feasibility and acceptability of using wearable cameras to objectively measure evening screen use including screen time, types of devices and activities, use of multiple screens, and the environmental context of screen use.

METHODS

Study Sample

Fifteen participants (aged 13−17 years) were recruited through personal networks, advertisements, and word of mouth, via parents or the adolescents themselves. Interested participants completed an online questionnaire; eligibility criteria included being a resident of Dunedin, New Zealand and aged between 13 and 17 years. Participants gave informed consent and additional parent consent for adolescents aged 13−14 years. Ethical approval was granted from the University of Otago Human Ethics Committee (reference 017/17).

Measures

Data were collected from September to December 2017, with 2 home visits for each participant. At Visit 1, participants were fitted with an accelerometer (Actigraph 3GTX) to wear for 7 days and nights on their nondominant wrist to measure sleep. Participants chose 2 weekdays and 1 weekend day suitable for wearing the camera at home from 5:00PM until ready to sleep.

The automated camera (Brinno TLC120, Brinno Inc, Taiwan) was programmed using a phone app (Brinno App) to take a photo every 15 seconds. The camera weighed 101 g, was 60 × 60 × 35mm in size, captured a 112° field of view, and could take photos in low light. The battery had a capacity of 10 days with a 15-second interval. Participants wore the camera on an adjustable lanyard on their upper chest secured with Velcro. Images were date−time stamped. Information booklets provided details about the places participants should remove or turn the camera off (e.g., bathroom or hospital), how to turn the camera off/on, and how to charge the camera if necessary. Participants practiced turning the camera off and restarting it and were given information cards for the public or friends and family to explain the study, if required.

The researcher completed a second visit at the end of 7 days. The camera converted the series of images to a time-lapse video (.avi) and created a new video every time the on/off button was pressed. On download to a laptop, the videos were converted to images (.jpeg) using the open source software FFmpeg (version 4.1.tar.bz2). Participants were offered the opportunity to view and delete images before the research team viewed them. The remaining images were stored on a high-capacity storage server only accessible to the research team.

To examine the acceptability of the study, participants were invited to complete an exit interview consisting of 9 questions at the end of Visit 2 (Appendix Table 1, available online). This interview took 5 minutes, including closed and open questions designed to elicit answers with respect to reasons for camera removal, family reaction, concerns about the study or improvements, and clarity of instructions (script in Appendix Table 1, available online). Participant answers were recorded on paper.

Images were coded using the open source software TimeLapse2 (version 2.1.0.6), which allows users to configure their own coding schemas and generate a database as images are coded. After a preliminary review of the images, a coding taxonomy was drafted to identify screens and associated activities. Images for the first 5 participants were coded by 2 researchers, and revisions to the taxonomy were made while a coding protocol was drafted. Coding continued until no additional changes were required to the coding taxonomy. A written coding protocol was produced, and the images recoded using the final coding taxonomy and written protocol.

Images for each participant were coded in 3 steps: (1) tagged as containing a screen or food or beverage, (2) filtered to only those containing screens and coded in detail (screen type, where, if the screen use was active or in the background), and (3) the type of screen activity (Appendix Figure 1, available online). Fifteen images could be displayed in the viewer simultaneously; images with phones were viewed individually. Blurry or obscured images because of the position of the participant while wearing the camera were tagged. Obscured images (such as those where the camera was facing the ceiling) in the middle of sequences of images containing screens were coded based on the nonobscured preceding and subsequent images. Figure 1 shows examples of images.

Statistical Analysis

Feasibility was examined by image quality, wear time, and codability of contextual factors (e.g., where screen use occurred). Acceptability was examined by compliance to the protocol and responses to the exit interview. For each interview question, responses were collated and summarized.

Stata, version 15 was used for descriptive analyses in 2018. Images captured after 5:00PM were included in the data set. Wear time (minutes) was calculated as the time between the first and last image. Captured time (minutes) was the number of images after 5:00PM divided by 4 (assuming each image represented 15 seconds). To determine the amount of data (time) lost because of participants turning the camera on and off or deleting images at the review stage, deleted time (minutes) was calculated as the difference between wear time and captured time. To determine compliance of wearing the camera until ready to sleep, potential

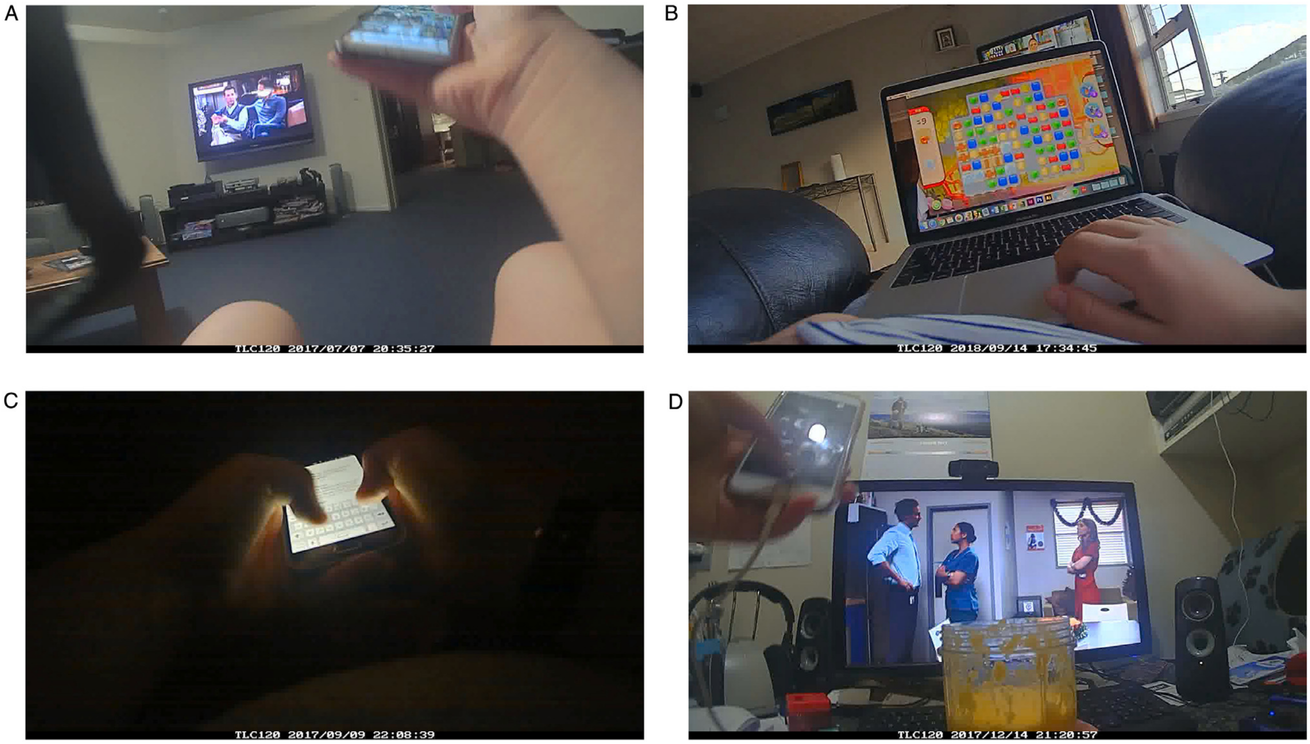

Figure 1. Sample of images and coding.
A, Primary screen, phone; Activity, uncodable; Secondary screen, TV; Activity, watching; Place, bedroom. B, Primary screen, laptop; Activity, gaming; Secondary screen, TV; Activity, watching; Place, living room. C, Primary screen, phone; Activity, texting; Place, bedroom. D, Primary screen, laptop; Activity, watching; Food, true.

wear time (minutes) was calculated from 5:00PM until the time of sleep onset (identified from actigraphy data). Compliance between days was compared using paired *t*-tests with $p<0.05$ indicative of statistical significance.

Images were repeat-coded for 4 randomly selected participants. Inter-rater reliability was assessed using κ statistics for the identification of primary screen activity and where screens were used.

RESULTS

Eleven of the 15 participants were female, 8 were aged 13–14 years, and 7 were aged ≥15 years. Mean age was 15.8 years (range, 13–17 years).

Thirty-nine evenings (of 45) were available for analyses, including 41,734 images. Losses were due to no images being available for 1 participant because they did not press the record button, and another participant did not wear the camera on Day 3. One participant wore the camera for <15 minutes on Day 1 and Day 3. The time to manually review images and tag all screens and food was 34 minutes per participant (SD=37 minutes), and 86 minutes (SD=65 minutes) for detailed coding of images containing screens. Agreement between coders for the types of devices was 87% and $\kappa=0.81$ ($p<0.001$). For the location of screen use, agreement was 93% and $\kappa=0.85$ ($p<0.001$).

On average, 1,050 images per evening were captured (263 minutes). Eight participants reviewed their images and 5 deleted at least 1. Time loss because of participants turning the camera off and on or deleting images was 14 minutes per evening. The mean number of dark images per evening was 1%, but this was highly skewed with only 7 evenings containing any dark images. For 1 participant, more than one third of the images were dark because of camera removal to a dark place. Less than 1% of images were blurry but 13% captured ceilings or floors owing to the participant lying on their back or front. The images for 2 participants did not have the correct time stamp because the camera had not been synchronized properly. Forty-five percent (SD=22%) of images contained screens and 8% contained food or beverages. The time spent viewing screens or using devices was 116 minutes per evening (Table 1). Wear time was significantly longer on Day 1 (296 minutes or 78% of evening time) than on Day 3 (244 minutes, 51% of evening time, $p<0.05$) but similar to Day 2 (288 minutes, 67% of evening time).

Table 2 shows the number and percentage of different screens and activities the screens were used for (if known) in the entire image set. The most common screens were phones (13.7%), TV (12.6%), and laptops

Table 1. Number of Images and Wear Time per Evening[a]

Variable	Mean (SD)	Minimum	25th percentile	Median	75th percentile	Maximum
Number of images	1,050 (399)	215	662	1,073	1,414	1,589
Time of first image, h:min	17:36 (1:04)	17:00	17:00	17:00	18:07	21:30
Time of last image, h:min	22:04 (1:07)	19:42	21:02	22:03	22:59	23:58
Wear time, min[b]	267 (97)	54	202	288	343	419
Captured time, min[c]	263 (100)	54	166	268	354	397
Deleted time, min[d]	14 (34)	0	0	0	16	190
Blurry images, %	1 (1)	0	0	0	0	5
Ceiling images, %	13 (14)	0	1	8	19	52
Dark images, %	1 (4)	0	0	0	0	21
Screen images, %	45 (22)	3	29	51	60	85
Screen time, min	116 (71)	11	70	111	165	240
Food images, %	8 (7)	0	3	6	11	25

[a]Included 39 evenings from 14 participants.
[b]Minutes between last image captured and first image captured.
[c]One image represents 15 seconds (number of images/4).
[d]Minutes camera was turned off by participant or an image deleted (wear time−captured time).
h, hour; min, minute.

(8.2%). For 11% of the phone images, specific activities could not be determined owing to inadequate resolution.

More than 5% of images contained multiple screens. The most common scenario was phones with TV or laptop in the background (Table 2). Phones were used on average 5.9 occasions per hour (SD=4.5). Participants switched between screen types (e.g., TV to phone) or from a screen to no screen (e.g., phone to no screen) 10 times per hour (SD=6.3).

As shown in Appendix Table 2 (available online), nearly all TV viewing (99%) occurred in the living room, whereas laptops (69%) and desktop computers (68%) were often used in bedrooms. Phones were used in all areas of the house and outside.

Six girls and 4 boys completed the exit interview. Only 1 participant had to charge the camera because it was flat, 5 reported charging the camera in case it went flat, and 5 participants reported using the information card. Nine agreed they would recommend the study to a friend. Responses to the open-ended questions are summarized in Table 3. The main reason reported for camera removal was to protect personal privacy. The most common suggestion for improving the study was to better secure the camera so it did not move around. Participants generally reported their family members were positive or neutral about the camera but 2 reported family members were conscious of the camera resulting in them feeling "embarrassed" and "invaded."

DISCUSSION

This study shows that automated cameras are a feasible research tool to use within homes to measure screen device use by adolescents. Nearly half of evening time was spent viewing or using devices, and there was evidence of multiple screen use for 5% of captured time. The context of screen use was able to be described (e.g., screen use in bedroom). Coding the activities for which the participants used their phone was challenging owing to poor image resolution, and this study has provided practical details to refine protocols. Uniquely, this study reports the time required to code images and quantified minimal data loss because of participants deleting images or turning the camera off.

Considerations of participant privacy, anonymity, and storage of data are important for all research; however, unique to using automated cameras is the capture of nonparticipants. An ethical framework for using automated cameras in research has been developed[21] and provides guidelines for researchers. Data loss because of dark images, turning the camera on and off, and deleting images was small (approximately 6%). It is common to provide participants with opportunities to review and delete images[13,22–26]; however, few studies have reported data loss because of this component, with the exception of Kerr et al.[11] who reported a "small number" of adult participants' deleted images. Automated cameras are a new research tool and therefore, understanding the sources of data loss is important. Minimizing privacy concern strategies, such as automatic blurring of faces, may be useful. Asking participants to record times when they turned the camera on and off and why (e.g., having a shower) might further minimize data loss.

The Brinno TLC120 performed well to measure screen use, a mainly sedentary behavior. It was reliable in low light and therefore suitable to measure screen use

Table 2. Description of Images Containing Screens

Screen/activity	Number of images (%)
No screen	22,405 (53.7)
Any screen	19,329 (46.3)
Single screen	
Phone	5,735 (13.7)
Unknown[a]	4,601 (11.0)
Watching	489 (1.2)
Texting/messaging	431 (1.0)
Gaming	107 (0.3)
TV	5,275 (12.6)
Watching	5,275 (12.6)
Laptop	3,432 (8.2)
Watching	2,294 (5.5)
Unknown	881 (2.1)
Music	82 (0.2)
Desktop	571 (1.4)
Gaming	383 (0.9)
Watching	156 (0.4)
Other	120 (0.3)
E-reader	62 (0.2)
Laptop (background)[b]	532 (1.3)
TV (background)	246 (0.6)
Phone (background)	228 (0.6)
Two screens	
Phone primary and TV secondary	1,418 (3.4)
Unknown and watching	778 (1.8)
Watching and watching	295 (0.7)
Texting and watching	190 (0.5)
Phone primary and laptop secondary	504 (1.2)
Unknown (both activities)	203 (0.5)
Unknown and watching	119 (0.2)
Laptop and TV	343 (0.8)
Gaming and watching	150 (0.4)
Survey and watching	87 (0.2)
Laptop and laptop	294 (0.7)
Gaming and unknown	191 (0.5)
Unknown and unknown	86 (0.2)
Phone and desktop	256 (0.6)
Unknown and watching	160 (0.4)
Unknown (both activities)	79 (0.2)

[a]Unknown is defined as unable to code the activity because of image resolution.
[b]Screen in background and turned on but participant engaged in another nonscreen activity.

before bed and in bed. Several limitations included blur when the participant moved and inadequate image resolution to code activity on phones. A new smaller model (Brinno TLC130) with attachable clips has become available and may be more suitable for research of active participants. Future research investigating phone activity may need to consider a higher-resolution camera or apps on the phone to log different activities.

The camera was ideally positioned for capturing screen use when the participant was upright or partially upright, but a relatively high percentage of images captured the ceiling when participants were on their backs. Other research using cameras to measure TV viewing time noted a similar problem.[20,27] Reviewing the photos with participants could help interpret obscured images. It may be beneficial to include a second camera to provide an overview of the entire room, although having a camera that points downward from a participant's viewpoint does mitigate privacy concerns of nonparticipants.[28]

Responses to the exit interview indicated a general acceptance to wearing the camera within their homes. It is not surprising most participants did not report any negative feedback from families as recruitment involved checking that the household agreed with the participant wearing a camera. The exit interview did reveal some family members may be more conscious of the camera presence than participants.

The findings showed approximately 5% of time was spent using multiple devices, switching focus from one device to another, or from a device to no device was frequent. Multitasking in this context might include using 2 screens in parallel, such as watching TV and browsing the web, or using one device and switching between activities, for example, homework and social media apps.[29] Few questionnaires are validated to measure media multitasking in adolescents. The Short Media Multitasking Measure measures the tendency of adolescents to multitask but does not measure the amount or combinations of multitasking.[30] In this study, switching between devices was measured but not number of switches between activities within a period of phone use. Automated cameras combined with apps on devices could track these data.

Limitations

The interviewed participants raised no major concerns regarding the study; however, they were interviewed by a researcher involved in the study and were not a randomly selected sample and may have been less critical. Others have reported lower recruitment (26%) in a similar age group for measuring the journey to and from school,[15] which may have been a barrier compared with this study's use at home. As there were more girls than boys in the study, less gaming and more phone use may have been captured, given known sex differences in these activities.[31] Nearly all participants wore the camera for 3 evenings, but wear time declined over the study. More than half of participants (n=8) were not attending school owing to examination study break or holidays; therefore, the finding may not reflect normal screen use. Not addressed was whether a 15-second time interval sufficiently captured all screen use; future work could

Table 3. Summary of Responses for the Exit Interview

Questions	Summary of responses (*n*)	Example of typical comments (P#)
Were there any situations or times when you had to remove the camera or turn the camera off?	For personal privacy (4)	"Going to the toilet and showering but did not have to remove because of people" (03)
	While working (2)	"When I was babysitting, I wore the camera but took it off when I was giving the child a bath" (08)
	To protect the camera (1)	"I needed to remove it while I was dying hair" (02)
Is there anything you think could be done to improve the way we are doing the study?	Secure the camera better to reduce camera movement (3)	"The camera was a bit wobbly and moved around while I was wearing it" (05)
	Communicate using e-mails (1)	"Send emails rather than text message- because of phone credit running out" (02)
What did your family think about you wearing the camera?	Curious and interested (2)	"They thought it was interesting" (03)
	Amused (1)	"Mum was ok with it she thought it was funny" (10)
	Conscious of camera presence (2)	"Dad was a bit embarrassed about having his photo on the camera" (01) "More aware than I was and a bit invaded" (07)

P#, participant number.

examine this with a continuous video or 1-second time intervals compared with longer intervals.

Little research exists examining reactivity to wearable cameras in children; qualitative research in older adults suggests camera removal may bias estimates of certain behaviors, such as removing the camera in social situations.[32] Of note was that on the first evening of wear, the camera was turned off more frequently (mean 2.2 times) than on the second (mean 1.4) or third evening (mean 1.3). Other research using automated cameras within the homes of young children reported caregivers noticed they became less aware of the camera toward the end of the study.[33] It is possible reactivity may be less of an issue for children and adolescents but caregivers could change how they parent, such as reducing screen time. The life stage of the participant, size of the camera (which varies considerably), and the length of wear may influence reactivity. Future qualitative research with children and caregivers who have recently worn cameras within a research study should be conducted to help inform the interpretation of collected data.

Important to the use of automated cameras in research is methods of coding the thousands of images.[17,34,35] TimeLapse2 offered a cost-effective option for coding images, but automated systems using artificial intelligence to recognize images[36] would greatly reduce researcher burden. Data from other technology worn with cameras, such as accelerometers,[12] have been used to identify where an image sequence for a behavior of interest starts and stops. A micro-camera has been developed that is activated with sounds associated with chewing and records a video sequence when someone is eating.[15] These advances could also hasten data coding and processing.

Questionnaires asking children to quantify screen use in a typical week rely on the child (or caregiver) being able to remember typical episodes of use, sum these, and distinguish primary from secondary activities.[37] Time use or media use diaries have a high respondent burden and short and simultaneous activities could be missed.[37] Automated cameras could be combined with other techniques to provide criterion validation or as part of a triangulation approach.

CONCLUSIONS

This research shows that automated cameras are a useful and acceptable tool to describe screen use and aspects of multitasking in adolescents. Researchers need to be aware they are not an easy alternative to other methods and should consider the functionality of the camera, autonomy of participants, and protecting nonparticipants. Further research is needed on reactivity, timing appropriate to research behaviors under study, and automation of coding.

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CS, BCG, RWT conceived the idea for the research. CS and WEdB collected data, developed the coding schema and coded images. CS completed analyses and drafted the paper. All authors contributed to interpreting results and revising the manuscript.

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SUPPLEMENTAL MATERIAL

Supplemental materials associated with this article can be found in the online version at https://doi.org/10.1016/j.amepre.2019.04.012.

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