NightLight: Passively Mapping Nighttime Sidewalk Light Data for Improved Pedestrian Routing

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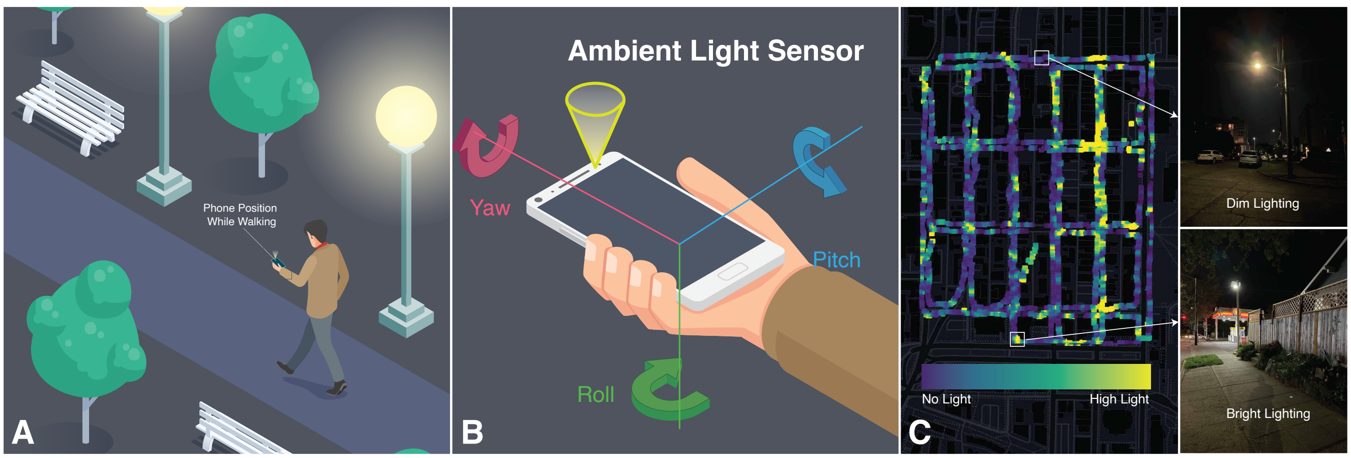

Figure 1: *Nightlight* leverages the ambient light sensors in smartphones to passively aggregate light level data for pedestrian navigation. (A) We observe that people generally orient their phone upwards while using their phone when they walk. (B) Combining the light readings from the light sensors with orientation context from the IMU and location from the GPS allows us to map the light levels on city streets as people walk. (C) We used Nightlight to map the light level in various neighborhoods to help identify dark and well-lit parts on a map which our user study indicated positively impacts pedestrian route choice.

Abstract

Nighttime sidewalk illumination has a significant and unequal influence on *where* and *whether* pedestrians walk at night. Despite the importance of pedestrian lighting, there is currently no approach for measuring and communicating how humans experience nighttime sidewalk light levels at scale. We introduce *NightLight*, a new sensing approach that leverages the ubiquity of smartphones by re-appropriating the built-in light sensor—traditionally used to adapt screen brightness—to sense pedestrian nighttime lighting conditions. We validated our technique through in-lab and street-based evaluations characterizing performance across phone orientation, phone model, and varying light levels demonstrating the ability to aggregate and map pedestrian-oriented light levels with unaltered smartphones. Additionally, to examine the impact of light level data on pedestrian route choice, we conducted a qualitative user study with 13 participants using a standard map *vs.* one with pedestrian lighting data from *NightLight*. Our findings demonstrate that people changed their routes in preference of well-light routes during nighttime walking. Our work has implications for improving personalized navigation, understanding pedestrian route choice, and expanding passive urban sensing.

*Both authors contributed equally to this research.

CHI '25, Yokohama, Japan

ACM ISBN 979-8-4007-1394-1/25/04
https://doi.org/10.1145/3706598.3714299

CCS Concepts

• **Human-centered computing** → **Mobile computing**; **Mobile devices**; **Smartphones**.

Keywords

Ambient Light, Pedestrian, Urban Informatics, Navigation, Mobile Sensing, Passive Sensing, Middleware

ACM Reference Format:
Joseph Breda, Daniel Campos Zamora, Shwetak Patel, and Jon E. Froehlich. 2025. NightLight: Passively Mapping Nighttime Sidewalk Light Data for Improved Pedestrian Routing. In *CHI Conference on Human Factors in Computing Systems (CHI '25), April 26–May 01, 2025, Yokohama, Japan.* ACM, New York, NY, USA, 13 pages. https://doi.org/10.1145/3706598.3714299

1 Introduction

> *Life happens on foot. People were created to walk, and all of life's events large and small develop when we walk among other people.* – **Jan Gehl**

Active mobility such as walking and bicycling provide numerous physical [25, 63], mental [38], social [3], and environmental benefits [58]. Due to the reduced visibility of pedestrian pathways and perceptions of safety, the presence or lack of urban lighting plays a critical role in shaping nighttime mobility by influencing *where*, *how*, and even *whether* people choose to travel at night [31, 51, 56, 80]. While modern mapping tools such as Google Maps and Apple Maps provide walking directions, they do not incorporate nighttime lighting conditions, leaving pedestrians in the dark. This is a missed opportunity to address the need, emphasized in prior work in HCI, for "*identity-situated pedestrian navigation*" [80] and move beyond efficiency as the sole criteria in pedestrian navigation [3]. A key limitation, however, is a lack of pedestrian-centeric lighting data.

One promising approach to sense and map urban lighting is through remote sensing, which analyzes illumination in nighttime satellite imagery [68, 83]. While useful for studying light pollution and economic indicators [78], these techniques are not precise enough to examine pedestrian-oriented lighting experiences at the sidewalk scale and can be outdated due to satellite flight patterns. Some cities provide open databases of street lighting locations [17, 65]; however, these datasets are typically focused on roads rather than sidewalks, do not capture other ambient light (*e.g.,* from businesses, awnings), and can also be out-of-date (*e.g.,* due to streetlight outages or new developments). Municipalities often offer civic engagement applications which allow residents to report such outages, but these rely on user engagement which can be difficult to scale and maintain [41, 70].

As a complementary approach, we introduce *NightLight*, a new passive smartphone-based sensing method that leverages the always-on ambient light sensor (ALS) built into smartphones—traditionally used for automatic screen brightness adjustment—to capture and map ambient lighting conditions as people walk while using their smartphones outdoors. As sensing middleware [37], we envision NightLight running in the background on phones, contributing data on sidewalk lighting conditions *as experienced* by pedestrians to open-source maps, including light from street lamps but also ambient conditions from storefronts, bus stops, and awnings.

As initial work, our goals are to demonstrate the feasibility of measuring nighttime lighting conditions with a smartphone, examine performance across sensing conditions, and understand how maps imbued with lighting information may impact pedestrian route choice. To pursue these goals, we conducted three studies: first, an in-lab technical evaluation to characterize light measurements across different phone models and orientations with respect to varying light intensities. Second, a controlled outdoor study walking on a 200 meter stretch of a city street with five streetlamps investigating the impact of distance, orientation, and location on NightLight with real-world lighting environments. Third and finally, we collected neighborhood-level data (covering 16.8 km total) with NightLight and conducted a qualitative user study (N=13) exploring how people plan and think about nighttime pedestrian routes with and without lighting data.

Towards the technical evaluations, our findings show that while ambient light sensors vary across smartphone models in respect to sampling rate, field of view (FoV), and sensitivity, they are comparable, in aggregate, to standard lux meters in measuring ambient light. Additionally, we find that orientation signals captured from the phone's built-in IMU and GPS location data introduces valuable context for understanding and mapping light levels, such as where the light is coming from relative to the user. For the user study, we found that most participants think about lighting and safety for nighttime walking and all participants actually changed their routes once provided with the NightLight infused map. All women indicated that this was particularly beneficial, especially when walking alone.

In summary, our work contributes to the growing literature in HCI and urban science exploring novel signals for improving personalized navigation [24, 33, 45, 59, 64, 66]. We make three primary contributions: (1) A passive and scalable smartphone-based technique called NightLight for sensing and mapping pedestrian-oriented ambient light levels; (2) Two technical evaluations in the lab and in real-world street environments validating our technique, including performance results related to phone orientation, phone model, and varying light levels; and, (3) Findings from a qualitative user study with 13 participants demonstrating that participants change their planned walking routes to favor well-light paths. NightLight has the potential to expand access to the benefits of active mobility by providing end-users with insight into pedestrian-oriented lighting conditions, meeting the needs of pedestrians populations that consider light levels, not just travel times.

2 Background and Related Work

We provide background on pedestrian lighting—covering lighting standards and prior work on how nighttime lighting shapes human mobility—before situating our work in street and pedestrian light sensing, participatory urban sensing, and pedestrian routing.

2.1 Pedestrian Lighting

Pedestrian lighting influences both route and transportation mode choice for nighttime mobility [3, 21, 34]. Because of street-level lighting's importance to vehicular and pedestrian safety, government organizations such as the *Illuminating Engineering Society* (IES), *Federal Highway Administration* (FHWA), and *American Association of State Highway and Transportation Officials* (AASHTO) set and study design standards [12]. While each differ slightly, a common recommendation is that the average illumination level for residential sidewalks should be at least 10 lux[1] and commercial streets should be greater than 15 lux with higher levels (20-30) at conflict points like crosswalks and intersections [1]. Two prior

[1] Lux is a unit of measurement for the intensity of light [36]; a higher lux value means a brighter area. For example, an work office may have a lux value of 300 while a brightly lit street may have a lux of 50 depending on the type of lighting, spacing, height, and the reflectivity of surrounding surfaces

studies examining perceptions of pedestrian safety and comfort with lighting found 10-15 [72] and 25-35 [48] lux as satisfactory. Additionally, a three-year long study of a 32-mile high-accident corridor in the US found that most traffic-related injuries occurred on segments with less than 10 lux [85]. Despite the influence of sidewalk ambient light levels on safety, comfort, and thus physical activity, there is still no scalable and fine-grained approach for measuring sidewalk light levels experienced by pedestrians across urban environments—a gap we begin to address in our work.

2.2 Sensing Street-level Lighting

There are four emerging sensing techniques for street-level lighting: (1) "smart" streetlamps that include sensor suites that can measure ambient light, assess light degradation, and serve as closed-loop feedback to centralized controllers for optimization [2, 57, 87]; (2) using fixed infrastructural cameras (like traffic cameras) combined with image processing techniques [79]; (3) mobile sensing approaches such as drones [6, 46] or sensor units (*e.g.,* cameras, LiDAR) attached to cars or bikes to inspect or identify light poles [5, 13, 73], and (4) remote sensing techniques using nighttime satellite imagery [68, 78, 83], as noted in the introduction. Each technique has trade-offs in terms of sensing granularity, update frequency, cost, governmental regulation, and human labor requirements. Most prior work is aimed at street-level lighting for vehicular traffic rather than pedestrian lighting or measuring light pollution [2, 73, 79]. Moreover, we are interested not just in infrastructural, government-installed lighting but in the actual ambient lighting experience of a pedestrian within the built environment including light from streetlamps but also businesses, awnings, bus stops, and other infrastructure. Our goal is not to replace these existing methods but to complement them.

2.3 Participatory Urban Sensing

NightLight is a type of participatory urban sensor [16], which leverages the growing pervasiveness of smartphones to serve as vast geo-located sensor networks. With an estimated 6.7 billion smartphone subscriptions worldwide [69], and some countries such as the US reaching over 90% penetration [19], this ubiquity offers a platform for easily scaling sensing systems. For example, smartphones can scalably monitor seismic activity [40, 76], human mobility [26], vehicular traffic flow [75], noise pollution [53], ambient air temperature [55], air quality [86], and more. So-called *participatory* or *crowdsensing* techniques [16] either work implicitly by leveraging the smartphone's built-in sensor suite to contribute data—such as the inertial measurement unit (IMU) in the *MyShake* seismology app [76]—or interactively by prompting the user to upload a geo-located picture [61], video [62], or text [74], which is potentially paired with the built-in sensor data.

While beneficial and increasingly common—*e.g.,* every Google Maps user implicitly contributes aggregate location data used to track and predict vehicle traffic conditions [27, 30]—there are key concerns with this approach including data coverage, smartphone performance impacts (*e.g.,* battery life), privacy, and incentivizing use [18]. Moreover, for those participatory sensing techniques that require explicit interaction, challenges include user annoyance, attrition, and self-report accuracy [77]. We designed NightLight as an implicit sensing solution, reappropriating the built-in ALS to automatically sense outdoor light levels when the user is outside.

2.4 Pedestrian Routing

Whether for packets or people, routing has long been a fundamental concern in computer science, typically focused on efficiency: what is the shortest or quickest path from A to B [8, 20]? More recent work in human mobility considers route recommendation as a multivariate problem, incorporating additional optimization criteria such as air quality and smell [60], noise [4], crime rates [52], traffic accident patterns [84], fuel efficiency [28], accessibility [32], point-of-interest popularity [47], and even perceptions of beauty, safety, quiet, and happiness [59]. Lighting in particular, has been demonstrated to impact perceived safety [31, 42], which can have powerful and uneven consequences: women report feeling unsafe walking at night more than men, and in turn, see as much as a 20% reduction in their nighttime physical activity [11, 22]. Our work contributes to this growing area but explores new methods for passively crowdsensing pedestrian lighting conditions and how such information may change route planning for pedestrians—to our knowledge, we are the first to do so.

3 NightLight

NightLight is a participatory light sensing approach that leverages the built-in light sensors on smartphones to passively sense and map outdoor lighting conditions as pedestrians travel with their phones out at night. NightLight is based on the intuition that as pedestrians travel through the built environment, they periodically check their phone to engage with messaging and navigation apps. During active phone engagement, users typical hold their phone angled up and towards their face, positioning the FoV of the phone's ambient light sensor (ALS) behind and above the user–providing good conditions to measure ambient light provided by overhead fixtures like streetlamps. Ambient light sensors use a light-sensitive module (usually a photo-diode) under the front screen which change resistance based on the surrounding light intensity within the FoV defined by the component housing. We designed Nightlight to leverage this sensor with the following considerations in mind:

- *Pedestrian-Oriented Data*: We aim to aggregate light levels *as experienced* by measuring light from the perspective of the pedestrian as they walk (i.e., lighting conditions of the sidewalk as opposed to vehicle lanes).
- *Passive Data Collection*: When pedestrians travel at night, they often use their phones for messaging, social media, and navigation. NightLight can leverage these interactions as opportunities to passively sense ambient light.
- *Leverage Existing Hardware*: We design NightLight to be entirely software-defined using just the sensors built-in to all smartphones to ensure scalability across the population. All sensors involved: the ALS, GPS, and IMU, are already activated in most navigation and mobile scenarios (i.e., using Google Maps) to adjust screen brightness, track location, and perform activity recognition, so the additional power requirements are minimal.
- *Data Coverage*: By leveraging the ubiquity of smartphones, we can scale data collection in regions with high pedestrian

density. Though NightLight can only collect data where people walk at night, it automatically prioritizes routes likely to be traveled by pedestrians. We envision NightLight as a complementary technique to the others enumerated in Section 2.2 but with the key advantage of measuring the actual lighting conditions for pedestrians.

3.1 Implementation

With these considerations in mind, we implemented an initial prototype of NightLight to collect and examine ambient light data. Though, we envision Nightlight running passively in middleware, for this paper we built an app for Android to log the ALS, GPS, and IMU data in the background using the Android sensor API. We acknowledge the technical simplicity of our approach but argue that this is a key strength for deployability as well as limits power and computational requirements. For example, we ran our app for 12 hours and saw only a 18% decrease in battery percentage during that time, indicating its feasability as middleware.

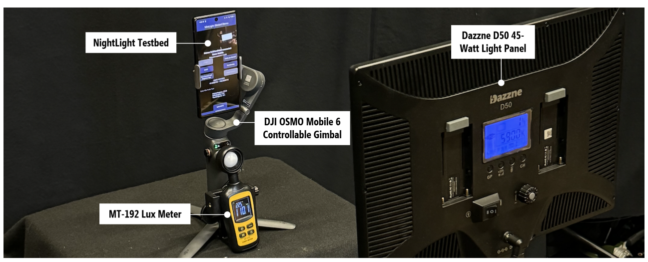

Figure 2: A visualization of our lab set-up including a dimmable *Dazzne D50* 45-watt light panel (40 cm x 40 cm) in a window-less dark room, a *DJI Osmo Mobile 6* to control the orientation of the smartphone, and a *MT-192* lux meter for measuring ground truth.

4 Study 1: Controlled Lab Evaluation

To examine the feasibility of using a smartphone for nighttime pedestrian light sensing, we conducted two controlled studies: first, an in-lab study to characterize light measurements across different phone models and orientations with respect to variable light intensities (described below); second, a controlled study examining NightLight performance in real-world pedestrian environments (Section 5).

For the controlled lab study, our goals were to examine and characterize how a smartphone's ambient light sensor functions compared to a lux meter (baseline) and to investigate performance as a function of device model and orientation. This study is motivated by two areas of prior work. First, smartphone sensing hardware and performance can vary across device models [15, 50, 67, 71], so we compared light measurements across four Android phones from three manufacturers: *Google Pixel 7* (2022), *Google Pixel 6a* (2021), *Samsung S8* (2017), and an *Essential PH-1* (2017). We intentionally selected models across price and age ranges, spanning $100-$500 USD and two to seven years old. Second, previous work shows that hand position and handedness can impact device orientation [9, 35, 82]. Due to the physical mechanics of how light sensors

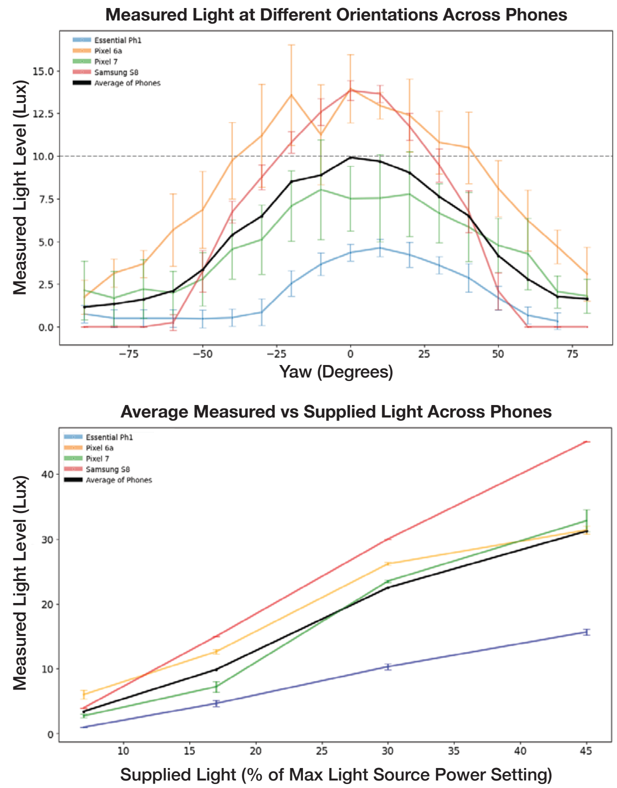

Figure 3: The plot on top displays the average light measurement across orientation angles for different smartphones compared to an external lux meter. When averaged across phones, the values match that of the commercial lux meter. On the bottom, is the measured light level across four smartphones—Google Pixel 6a, Pixel 7, Samsung S8, and Essential PH1— across the intensity of the light source at a perpendicular orientation. When averaged across phones, the lux measured match that of the commercial lux meter at aimed directly at the light source

operate, light rays hitting the sensor at a more perpendicular angle lead to a greater measured intensity. We therefore characterize and compare the light intensity across the entire FoV at different light levels for each of these phones in a common environment.

4.1 Lab Study Method

We conducted the lab study in a window-less dark room with a dimmable *Dazzne D50* 45-watt light panel (40 cm x 40 cm) located 3.8 meters from the study device (smartphone) and a commercial *MT-192* lux meter (for ground truth)—see Figure 2. To programmatically control the orientation of phone during each test, we used a a *DJI Osmo Mobile 6* gimbal mount. While logging ALS data, our custom NightLight testbed software ran a controlled sweep from -10 – 30° across the pitch axis (X rotation)[2] and -90 – 90° in the yaw axis (Y rotation)—see the axes illustrations in Figure 1B. For each phone,

[2]The pitch axis was mechanically limited to -10 – 30° by the gimbal design.

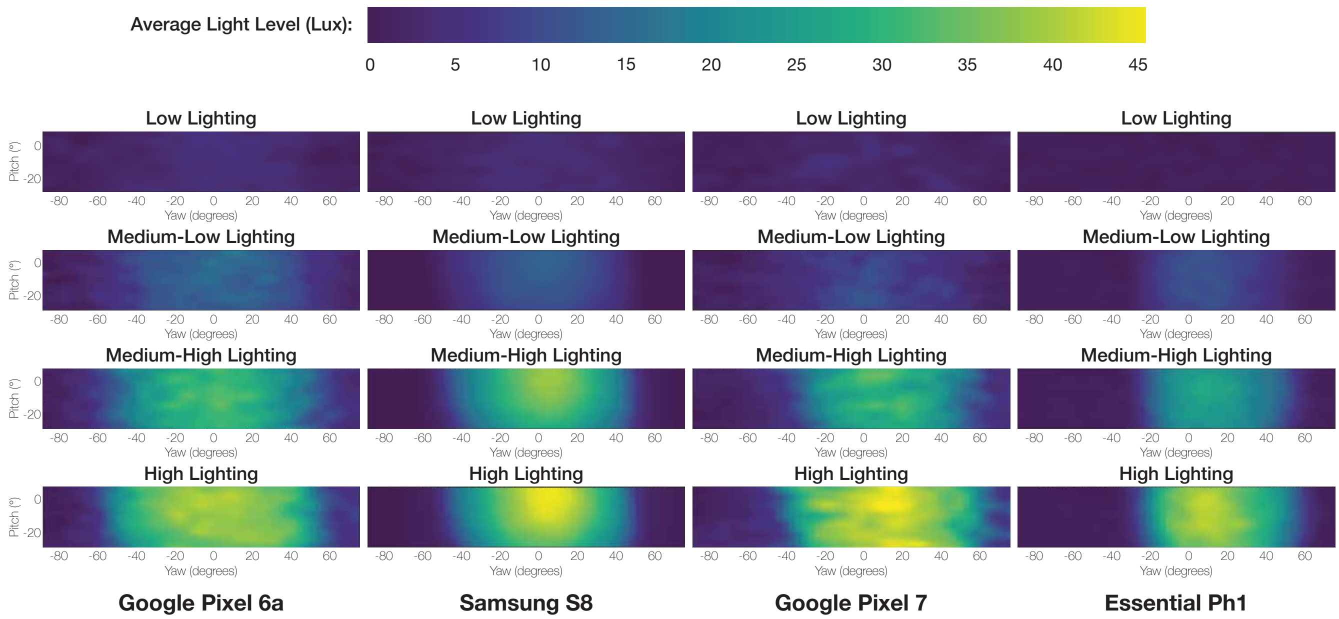

Figure 4: We generated heat maps for various smartphones under different lighting conditions: low (2.5 lux), medium-low (10 lux), medium-high (20 lux), and high (30 lux). The different spread of the heatmaps indicate that some phones have narrower FoV for their ambient light sensor, like the Samsung S8 and Essential Ph1. The smoothness of heatmap reflects a higher refresh rate, with the Samsung S8 demonstrating a much higher sampling rate compared to the other devices.

we collected three sweeps at four light levels, informed by related work [48, 72], measured on the commercial lux meter: low (2.5 lux), medium-low (10 lux), medium-high (20 lux), and high (30 lux).

4.2 Lab Study Results

Overall, we found that phones had different "offsets", sensitivity, and refresh rates that impacted the light readings but on aggregate, performed comparatively to the commercial light meter. Below, we describe key findings related to performance differences across phones and gimbal orientations.

Comparison Across Phones. Our tests indicate that although different phone sensors have differing gain, offset, and consistency, they all show a similarly linear trend, and that when averaged across phones, the aggregate signal closely approximates the commercial light meter reading. Figure 3 (top) shows the light readings aggregated across trials from each phone during the sweep from -90 – 90° in the yaw axis while the pitch axis remained centered at 0° at a fixed light intensity of 10 lux. This demonstrates that different phones have reproducibly different intensities at different orientations relative to the measured light source, though share a similar trend. Interestingly, we found that averaging all phones at the center position (0° yaw) resulted in the same measurement as the commercial lux meter. Similarly, Figure 3 (bottom) shows the lux measured by each phone at 0° pitch and yaw across different light intensities, averaged across all trials.

Comparison Across Orientations. The orientation of the phone has a significant impact on the ALS readings, reinforcing the importance of incorporating IMU data into NightLight. That is, the measured lux is weaker as the light source moves closer to the peripheral of the ALS FoV. This is shown in Figure 4, as a series of heatmaps of the measured light levels for each phone at various orientations. Our tests validate the importance of tracking and integrating phone orientation when aggregating the data. Specifically, our results show that the Google Pixel 6a and Pixel 7 smartphones have a wider FoV (shown with a more gradual taper at the edges) and the Samsung S8 and Essential phones have a narrower one. The heatmap is also influenced by the sample rate of the phone's ALS, where slower sample rate leads to more noise in the data (i.e., a grainier heat map like that of the Pixel phones).

5 Study 2: Controlled Street-based Validation

Having characterized ALS performance and demonstrated initial feasibility, our Study 2 goal is to examine performance more naturalistically: walking down city streets. To accurately measure geo-located light in this context, we need to account for device orientation and light location (*e.g.*, if you tilt the phone from the light source, the ALS sensor reading will decrease as demonstrated in Study 1). Thus, Study 2 investigates how to integrate and process the phone's IMU data and GPS over time to infer light source locations, which is key to appropriately map light level data.

5.1 Study Method

To better understand the interplay between the orientation, location, and magnitude of measured light in a street environment, we conducted two experiments with the Google Pixel 6a (representing a "mid-range" option from phones characterized in study 1). First,

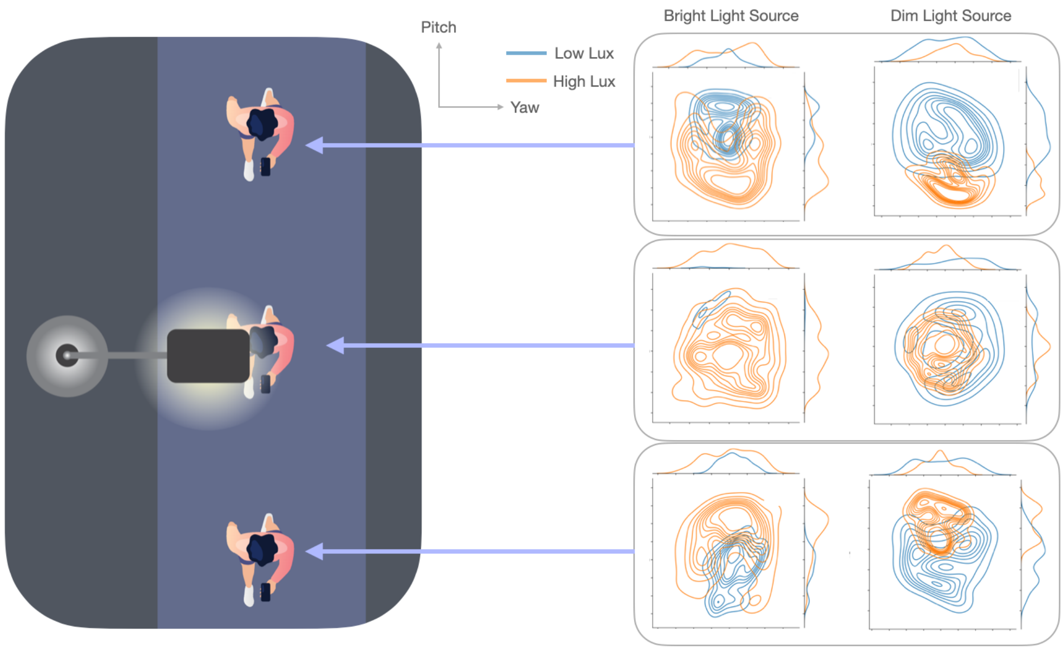

Figure 5: Density of high light measurements (above 2 lux in an outdoor environment) and low light measurements (below 2 lux) across the roll and pitch axes (centered at 0 degrees) when standing behind, under, and in front of the light source at fixed distances for bright and dim light sources. The bright light sources have a higher density of high light measurements than the dim light sources and the high light values are saturated off-center and in the direction of the light source when the user is at a distance.

we varied the orientation continuously and arbitrarily at fixed locations: adjacent to and both one meter and three meters in-front and behind a variety of streetlamps and analyzed the distributions of high and low lux across these orientations at different positions relative to the streetlamp. Second, we held the phone at a steady orientation towards the user's face while walking a 200 meter stretch of street in both directions (East and West) three times each. We then investigate the patterns in the ALS readings during the phone's trajectory with respect to the known streetlamp locations along this street pulled from Seattle's city open-data portal [65].

5.2 Study Findings

Overall, we found that the orientation and location timeseries added valuable spatial context to the ALS readings, e.g., which direction the light is coming from. This is important when the orientation of the device is subject to natural variation due to motion during use, resulting in the ALS FoV aiming at, and potentially capturing, distant light sources not affecting the immediate local light level.

Orientation. Intuitively, we found the highest lux values to correlate most with rotation vectors angled towards the light post (i.e. if we were standing before the streetlamp, the high lux values were saturated at a positive pitch angling the ALS away from the holder and towards the streetlamp, while the opposite was true when standing after from the streetlamp). The saturation of high and low lux values at different rotation angles and positions relative to the streetlamp are visualized in Figure 5. This demonstrates that the ALS's sensitivity to rotation can be leveraged to inform the relative location of nearby light sources as the orientation measured by the IMU, corresponding to the highest lux measurement represents when the ALS FoV is aimed at the light source.

Location. We find a similar pattern in measured lux at different distances from light sources. The instantaneous heading of successive GPS coordinates i an $i + 1$ along our walks can be calculated to determine the compass direction of travel at each location. We then use the processing outlined in Figure 6 to extract the region of time when the phone holder is before and after the nearest streetlamp on their walk. Aggregating the lux measured across all walks at different distances before and after each streetlamp reveals the trend in Figure 6. The maximum lux recorded occurs some distance after passing the overhead light source, when the streetlamp is both above and somewhat behind the user and aligned within the ALS's FoV. This demonstrates the impact of relative distance of light sources on NightLight data.

6 Study 3: Qualitative User Study

Having evaluated the technical feasibility of collecting NightLight data, we shift our attention to study the utility and impact of NightLight to pedestrians walking at night. We used the NightLight app to collect neighborhood-scale light level data across three neighborhoods of Seattle. We then use the maps generated by this data, shown in Figure 7, to conduct a qualitative study examining people's perceptions of nighttime walking, factors influencing route

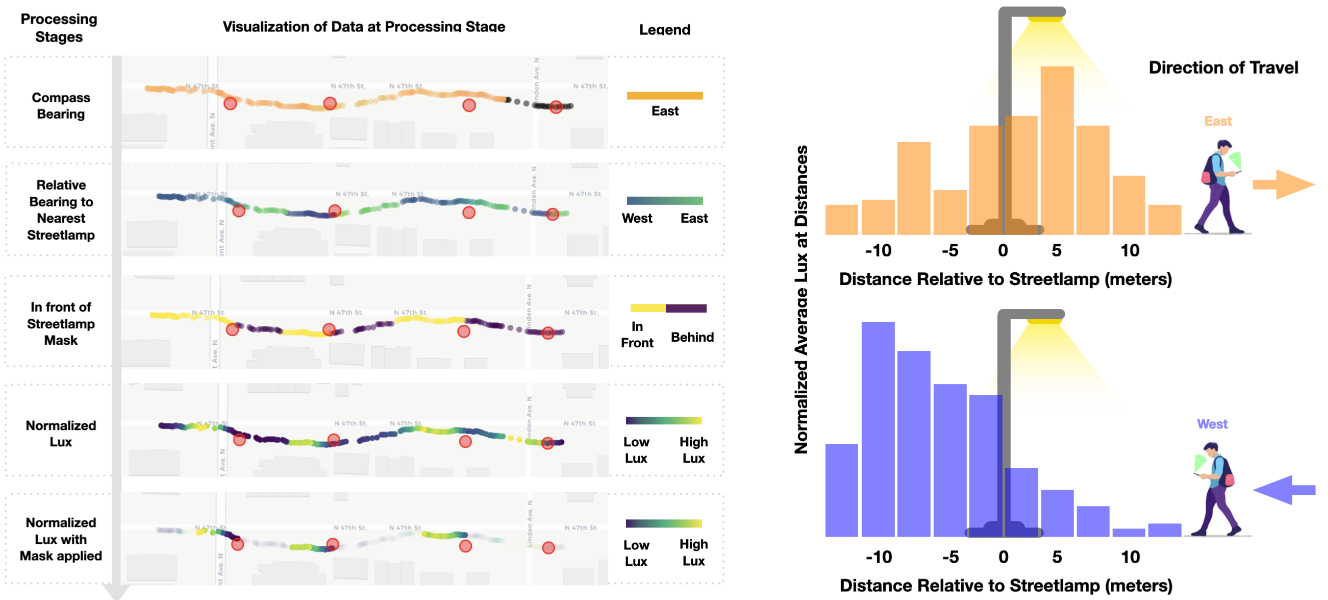

Figure 6: (left) A visual representation of the stages of processing to isolate the lux values corresponding to known streetlamp locations. (right) The average normalized lux at different signed distances approaching and passing the streetlamps along the street in both directions of travel (East and West). Negative distances represents the user West of the streetlamp and higher distances represent the user East of the streetlamp. The normalized lux is maximized after crossing the position of the streetlamp positioning it behind the user and in the ALS FoV.

choice, and how participants engage in a nighttime route planning task with and without a NightLight-infused map.

6.1 Neighborhood Scale Data Collection

With NightLight installed on Google Pixel 6a devices (same as Study 2), two authors and a third member of the research lab separately collected light data for three different neighborhoods which we refer to as: Waterfront, Gridded, and Residential, covering a total distance of 16.8 km. We selected neighborhoods to capture variations in layout, infrastructure, and zoning. The Waterfront neighborhood is a commercial hub with irregularly angled streets and a multiuse walking path along the water offering trade-offs between aesthetics, brightness, and distance. The Gridded neighborhood features a traditional urban layout with uniform distances between routes, parks along some perimeter roads, and a historic landmark street with pedestrian-oriented lighting. The Residential neighborhood contrasts with darker streets and a major arterial road, emphasizing a trade-off between the shortest route and better-lit alternatives. The data was collected across multiple nights between the hours of 10pm and 1am while walking normally, holding the phone slightly up and towards the user's body.

6.2 Participants

We recruited 13 participants (6 male, 6 female, 1 non-binary) through convenience sampling at a university (Table 1). Our recruitment materials advertised that our study focused on nighttime walking behaviors. Most participants were adults in their early 20s to mid 30s who relied on public transit and walking as their primary mode of transportation. Ten participants indicated that they walk daily, primarily walking more during the day than at night. All but three participants indicated discomfort with walking at night, with non-male participants skewing more uncomfortable. Three participants recognized at least one of the three neighborhoods in the study. None of the participants recognized the Residential neighborhood.

6.3 Qualitative Study Method

Study sessions were divided into three parts. In Part 1, we collected demographics and asked about day and nighttime walking behaviors. In Part 2, participants completed a comparative route planning task with and without lighting condition data across three neighborhoods using printed maps (Figure 8). For each neighborhood, we asked participants to hand draw and "think-aloud" about their preferred route for two different origin-destination pairs (resulting in six total routes). We counterbalanced neighborhood order and presented the map with no lighting data before the NightLight-infused map. Participants could also indicate that they were not comfortable walking at a particular location at night and discuss how they might seek alternative transport. Finally, in Part 3, we performed a debrief interview soliciting feedback on the value of nighttime lighting data and future navigation tools. All study sessions were audio recorded and conducted in person. One researcher led the session while the other took notes. For analysis, we qualitatively coded session data using Thematic Analysis [14].

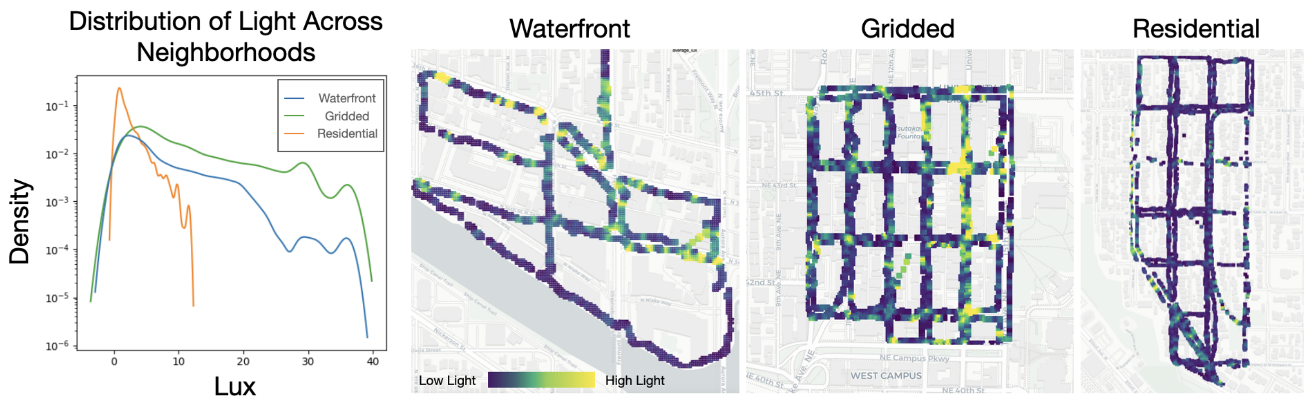

Figure 7: The sidewalk light data collected across the three sample neighborhoods along with a log-scale kernelized density estimate, showing the density of light levels across individual ALS readings captured in all three neighborhoods. The Residential neighborhood has notably lower lux across all readings while the Gridded neighborhood has slightly more high lux locations than the Waterfront neighborhood.

6.4 Qualitative Study Results

We describe our results organized by the three study parts: factors influencing nighttime walking behaviors, the comparative route planning task, and the debrief reflection. Quotes have been lightly edited for clarity and concision.

6.4.1 *Nighttime Walking*.

When asked about nighttime walking and route choices, our participants emphasized the presence of others, the design of the surrounding built environment, lighting, route simplicity, and safety. For most, safety was a cross-cutting concern, which was often inferred from other factors. We discuss these factors below.

Time of Day. All participants reported walking less at night. However, non-binary and female participants reported feeling significantly less comfortable than male participants. Of the nine participants who commute daily by walking, biking, or using public transit, half of the female participants reported rarely or never walking at night, whereas the male participants either maintained or slightly reduced their night walking frequency. P4 stated they purposely avoid walking at night as much as they can: *"the amount of times I've walked at night has decreased year by year...just in general I'm not really out at night after dark."*. The choice of route itself was also influenced by time-of-day: "*During the day I have no issue taking the quieter streets but at night I like to stick to the larger streets in case something happens.*" (P5).

Presence of Others. Most commonly, participants mentioned the expected level of pedestrian traffic and street activity (*e.g.,* from street dining and others commuting) along a route, often stemming from safety concerns. As P2 said, "*I see other people walking there... [so] it must be fine to walk here*" and P1: "*I would rather walk along a busy street than one of those residential streets, which has much fewer people on it.*" Similarly, P11 said, "*I really don't want to walk on a route that's dark and isolated. Is the street populated? Am I gonna get mugged? Is anyone gonna hear me?*"

The Built Environment. The surrounding built environment also played a role, including the width and types of streets, the proximity to points-of-interests (*e.g.,* bus stops, restaurants), presence of green space, and zone type (*e.g.,* commercial *vs.* residential). As P10 stated, "*Mainly, I want to walk where businesses are open... Like in Apple Maps where it shows commercial zones, that matters more to me than how long the route is.*" and P9 said: "*I'm not going to take any back alley roads or weird shortcuts.*" Participants also noted tradeoffs between busier well-lit main roads and an increase automobile traffic: "*I prefer the main road, but heavy car traffic is bad because at night I don't want to get hit, but without other information, I'll still probably take it*" (P11).

Lighting. The availability and quality of lighting across routes was also important, and most female participants brought up lighting even before it was revealed as the study subject: P11 "*If I was in a situation where I had to walk at night, my primary concern is whether there is enough light.*" and P9 similarly said: "*If I absolutely had to walk, I would take the best lit route...[which likely corresponds] to the one with more students and people.*" After seeing the NightLight data most participants, like P2, commented on how lighting indicates presence of others: *"Lighting is a useful proxy for the area being more populated and developed."* For P3, NightLight data made walking feasible when she had previously opted for rideshare *"With this data, I now know this route is not completely dark, so I am now more likely to walk this route than take an Uber"*. This directly demonstrates the utility of NightLight for broadening access to active mobility.

Route Complexity. Finally, participants mentioned route complexity as a factor, preferring simpler routes to reduce travel time and ease navigation. For male participants like P2, simplicity was about efficiency *"I would avoid unnecessary turns just because I can pay less attention"*, whereas for female participants, simplicity was about safety. As P3 said, *"the more straightforward the better. I avoid zigzag routes because then I need to keep looking at Google Maps, which consumes battery and is scary. I also want to be observant of my surroundings at night"* (P3).

Participant	Age	Gender	Occupation	Primary Mode	Walks	Night Walks	Comfort At Night
P1	25-34	Male	Grad Student	Bicycle	Daily	Daily	Comfortable
P2	25-34	Male	Grad Student	Walk/Public Transport	Daily	Daily	Comfortable
P3	25-34	Female	Grad Student	Walk/Public Transport	Weekly	Rarely	Very Uncomfortable
P4	25-34	Non-Binary	Grad Student	Walk	Daily	Never	Very Uncomfortable
P5	18-24	Female	Grad Student	Walk/Public Transport	Daily	Weekly	Somewhat Uncomfortable
P6	18-24	Female	Grad Student	Car	Weekly	Weekly	Very Uncomfortable
P7	25-34	Male	Grad Student	Public Transport	Daily	Weekly	Somewhat Uncomfortable
P8	25-34	Male	Grad Student	Bicycle	Daily	Weekly	Comfortable
P9	18-24	Female	Grad Student	Walk/Public Transport	Daily	Rarely	Very Uncomfortable
P10	25-34	Female	Finance Manager	Public Transport	Daily	Weekly	Somewhat Uncomfortable
P11	25-34	Female	Grad Student	Public Transport	Daily	Rarely	Very Uncomfortable
P12	18-24	Male	Grad Student	Car	Rarely	Never	Somewhat Uncomfortable
P13	18-24	Male	Grad Student	Car	Rarely	Rarely	Somewhat Uncomfortable

Table 1: Background characteristics of our 13 interview participants.

6.4.2 ***Route Planning Task***. For the route planning task, we asked participants to hand draw a route while "thinking aloud" across six origin-destination pairs on paper maps with and without lighting data. Overall, participants used visual cues from the maps to inform their route choice, including the width of streets and the presence of businesses combined with efficiency, route simplicity, and, for the NightLight-infused maps, the presence of lighting data. We found that pedestrian light information on a map significantly influenced route choice: participants changed 50/72 routes (69.4%) to follow a more lit path. Without the light data, participants drew routes that attempted to optimize for efficiency and safety using visual map cues (*e.g.,* size of road, type of buildings visible). With the NightLight-infused versions, participants primarily followed the brightest path, even at the cost of efficiency—see Figure 8. For example, for the first origin-destination pair in the gridded neighborhood, most participants drew a simple northbound to eastbound route with one turn; however, with the lighting data, all participants switched their routes, even at a cost of route simplicity.

When participants did *not* change their routes as a result of lighting data, they often cited the tradeoff of travel time. This was particularly common for the first origin-destination pair in the residential neighborhood where most participants drew a straight northbound route with and without lighting data because the lit route was 1.4x longer (0.7 *vs.* 1.0km). Interestingly, despite this additional effort and time cost, three participants still followed the longer, better-lit route.

6.4.3 ***Debrief and Future Technology***. Finally, we engaged participants in a debrief interview soliciting feedback on the utility of lighting data and the future design of navigation tools. In general, participants felt that the lighting data was useful, particularly for female, single travelers, and those in unfamiliar areas, and that future mapping tools should factor in lighting with route recommendations or include an optional light layers. As P2 said, "*I've definitely had experiences where maps route me down a dark, isolated path and I've been like, 'ugh... I don't know about this.' Particularly on urban waterfronts which can either be very pleasant and well-lit or totally lack night infrastructure*" Participants desired algorithmic transparency—what factors are navigation tools using to recommend routes: "*These apps tell you where to go but it doesn't tell you why... [it could say], 'walk this safer route even though its longer'*" (P10). Others suggested that this data could be useful to city governments, helping "*the city find out where to put more lights*" (P9). Some mentioned the data would even be useful as a driver *"when I drive at night, my primary concern is hitting a pedestrian. This could help me protect others"* (P11).

7 Discussion

In this paper, we introduced a novel sensing technique, called *NightLight*, to passively measure ambient light conditions experienced by pedestrians as they walk at night. Using a multi-methods approach across three studies, we demonstrate technical feasibility, highlight performance characteristics, and show the utility of NightLight-infused maps on route planning. Below, we discuss scalability, nighttime route choice, potential social implications, and technical improvements of our work.

Scalability. Our technical evaluations showed that a smartphone's built-in ALS sensor functions similarly to a commercial lux sensor and that we can robustly measure ambient pedestrian lighting. However, to comprehensively map lighting data, our approach is dependent on *where* people walk at night, *how often* they pull out their phones, and *how many* people walk along pedestrian pathways. Though NightLight's sensing granularity and measurement of actually experienced light levels are key strengths, our approach will likely work best for densely populated regions. Gamification [54] or organized efforts from activist communities—similar to the efforts of War-Drivers in the early stages of location tracking [43]—could bootstrap light-level datasets for unmapped areas. Though, as we observed in our user study, pedestrians will begin favoring well-lit paths once a NightLight-like technique is integrated and visualized in routing applications. This could undermine data collection. Thus, we envision NightLight as a complementary approach to other emerging methods, such as "smart" streetlamps [2, 57, 87] and fixed infrastructural cameras [79]. Through a deployment study, future work should explore how many users are necessary to reach sufficient data coverage and aggregation while preserving individual user privacy. The deployed system could use methods to obtain consent and anonymize aggregated user data from prior work in opt-in crowdsourced systems [10, 81]. The deployment study could also measure variation in light levels for the same locations over time based on, for example, whether proximal business lighting is on/off, the presence/absence of car headlights, or even lunar phases. As NightLight produces a measure of light across both space and time, future work can investigate the cadence with which light levels change (i.e., businesses close or streetlight outages).

Nighttime route choice. In our user study, we found that pedestrian light information significantly informed route choice—nearly

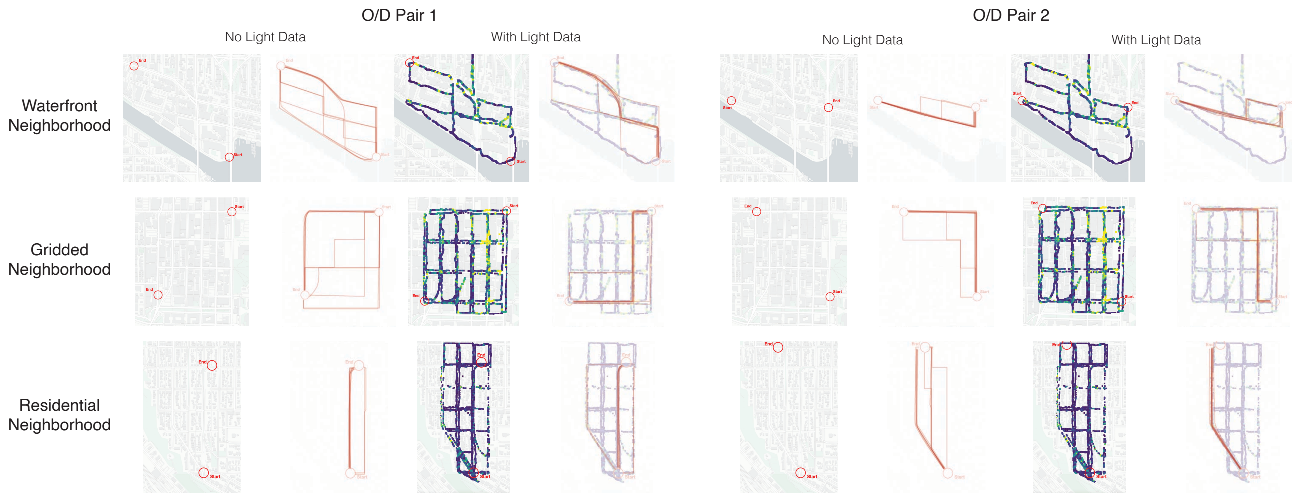

Figure 8: Participants were asked to draw routes between origin-destination (O/D) pairs with and without NightLight data. For each O/D pair, without and with light data in each neighborhood, the map provided to participants appears to the left and an aggregation of all routes drawn by participants appears to the right in red. Darker lines indicates chosen routes shared by a larger portion of the study population. Without light data, participants drew routes optimizing safety and efficiency based on visual map cues (*e.g.,* road width). With the light data, most routes (50 of 72) changed to follow the brightest path.

70% of planned walking routes (50/72) were different in the NightLight map condition. While no previous studies have examined how pedestrian lighting specifically influences nighttime route planning, prior survey and observational studies found that people prefer well-illuminated streets for nighttime walking. Lighting increases sidewalk visibility, but more importantly, provides feelings of increased safety [51, 56]. Though lighting is clearly a critical factor, our study findings also highlight the complexity of human behavior and nighttime route choice, incorporating factors such as the expected presence of others, the amount of vehicular traffic, the width and type of streets, the existence and type of business and transit stops along a route, and the complexity of a route itself remain important. In addition, prior work emphasizes the need for other factors not mentioned by our participants, such as the accessibility of a route to people with disabilities [23, 32]. Future work on nighttime navigation and mapping tools should incorporate and study these additional factors.

Potential Externalities. NightLight aims to improve pedestrian navigation through integrating knowledge of preferred lighting conditions. However, this information has the potential to significantly alter the ways users interface with the built environment by discouraging engagement with poorly-lit neighborhoods. Lefebvre's theorized that space is a social construct and is actively produced through social perceptions and the people who occupy it [44], therefore it is important to consider how navigation platforms have the power to shape or bias the meaning of urban space. For example, by navigating users away from poorly-lit neighborhoods which may be historically under served [3, 39]. Additionally, access to NightLight data could pressure municipalities to increase streetlighting which has both economic and environmental costs through contributing to "light pollution", which can impact local species and natural ecosystems [49], and consume additional energy.

Technique improvements. There are several technical improvements to NightLight including cross-user calibration, activity recognition, and additional sensor data. In Section 4 we uncovered a difference in light measured across phones in the same environment. These cross-device differences could be calibrated using real-world data when NightLight users with different phone models cross paths, providing a standardized environment to calibrate against. Additionally, more complex models could be used to capture 3D light maps as NightLight users traverse the same routes while holding their phones in different orientations (*i.e.*, inverse ray-tracing), revealing variation in light on different sides of the route. Future work can leverage the front-facing and rear-facing camera to add additional context about the device proximity to the user, occlusion, and other environmental features to model the effects of light reflected off the user. Future versions could further leverage IMU and location data for activity inference, such as walking, biking, and running [7, 29] to either filter or tag NightLight data with additional context—for example, to avoid collecting nighttime light data while traveling inside a vehicle. The ALS hardware can measure more than just lux, they can log light temperature, infrared light level, and full spectrum light levels. However, that information is restricted by the operating system. Access to this data could gain richer insights about the amount and the *kind* of light experienced by pedestrians.

Limitations and future work. Beyond technical improvements to the sensing technique, there are several limitations opportunities for future work. First, while our work demonstrated the feasibility of passively mapping ambient light data with a smartphone and the utility of such data to pedestrians, we did not conduct a deployment study to evaluate NightLight with end-users and examine end-user contributed data. Such a study could reveal the effects of pedestrian phone usage patterns and provide a dataset which could to perform cross-device calibration. Second, we provided our participants with map of light data so they can make their own route, but future systems could implement a routing algorithm that automatically directs them to the most well-light path. Lastly, Our participant pool was largely composed of college students drawn from a single city. To address these limitations, future work should perform a deployment study and recruit a more diverse user pool. Our user study surfaced additional use cases for NightLight data in infrastructure maintenance and for non-pedestrians that are worth pursuing in future work. For example, NightLight could help municipal governments and agencies identity and maintain public utilities and lighting infrastructure without relying on manual reporting or auditing. Moreover, as P11 noted, there are other users who may want to know light level data like drivers, runners, and cyclists. Future work could adapt NightLight to capture light on bike lanes and roads to suggest well-light routes for cyclists and driving routes with better road lighting conditions to help drivers feel more secure and avoid areas where they may have collisions due to low visibility.

8 Conclusion

In this paper we presented NightLight, a sensing middleware paradigm envisioned to run passively on pedestrian's smartphones while on outdoor walks to passively crowdsense pedestrian lighting conditions. We conducted two controlled technical validation studies: first of the ALS on four smartphones across varying light level and phone orientation in a lab setting, and second, on data collected from controlled walks on real-world streets. We then collected a neighborhood scale NightLight maps which we used as prompts during a 13 user interview study to access how NightLight data impacts pedestrian route choice. These studies reveal the technical feasibility of deploying NightLight across smartphones and indicate that the data produced by NightLight deployments can improve the quality of pedestrian routing by providing well-lit routes that match some user's preference. This work contributes to the growing field of pedestrian-oriented navigation and shows that our technique can collect meaningful urban lighting data that positively influences pedestrians preferred navigation routes.

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