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Evaluation of Sensor Technology for Street Lighting

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Table of Acronyms

Abbreviation	Meaning
AI	Artificial Intelligence
AIR	Active Infrared
CCD	Charge-coupled device
Cir	Circle
CW	Continuous wave
FMCW	Frequency-modulated continuous-wave
Light detection and ranging	LiDAR
NIR	Near infrared
PIR	Passive infrared
RCS	Radar cross section
Rect	Rectangle
TOF	Time of Flight
ΔT	Thermal contrast

INTRODUCTION

Outdoor lighting alone accounts for ~15–19% of global electricity consumption (Bachanek et al., 2021). Smart street lighting can use occupancy sensors to adapt light levels to user presence, reducing energy use substantially, with reported savings approaching ~80% in optimized deployments (Pazzini et al., 2024). Dimming strategies can also mitigate skyglow, glare, and light trespass while reducing operational stress and potentially extending system lifetime (IEEE Smart Lighting, 2025; Wilson et al., 2023).

However, reliable occupancy detection outdoors remains challenging. Unlike stable, bounded indoor environments, outdoor sites expose sensors to weather, illumination extremes, background motion, mixed road user types and diverse movement patterns that can affect detection performance (Avotins et al., 2014; Azizi et al., 2021). Moreover, much of the rigorous sensor-performance literature focuses on indoor environments, with fewer standardized outdoor evaluations (Agramelal et al., 2023; Fahim et al., 2021; Mahoor et al., 2020).

Occupancy sensors are a critical component of adaptive lighting systems because the lighting response depends on when, where, and how consistently users are detected. In street and area lighting applications, the sensor should detect pedestrians, cyclists, vehicles, and other users early enough and across a sufficient area to allow the lighting system to provide a continuous illuminated path. Ideally, the detection area should align with, or extend beyond, the illuminated area. If the detection footprint is too small, poorly aligned, or delayed relative to the user's movement, the lighting system may not provide the intended visibility benefit. Conversely, excessive false detections or prolonged activation after the user has left may reduce expected energy savings.

The primary goal of this study was to evaluate the detection performance and spatial coverage characteristics of outdoor occupancy sensors used in street and area lighting applications under controlled outdoor test conditions. The experiment characterized how different sensing technologies responded to different road-user types, movement relative to the sensor, ambient temperatures, and mounting heights. Understanding these relationships can support evidence-based guidance for sensor selection, placement, and integration into roadway lighting systems.

LITERATURE REVIEW

To provide context for the experimental evaluation, a literature and industry review was conducted. The review synthesized peer-reviewed evidence on sensing modalities used for outdoor occupancy detection, reviewed the commercial market for products implementing these modalities, and extracted comparable product specifications such as road-user recognition capability, detection range, coverage angle, and mounting height. The review also compiled

findings from prior evaluation studies of outdoor occupancy sensing technologies, including their methods, reported performance, and limitations.

OUTDOOR OCCUPANCY SENSING SYSTEMS

Occupancy Sensing Technology

An occupancy sensor is a device that detects the presence or absence of people or vehicles in a defined space by sensing physical signals (e.g., infrared radiation, radio waves, thermal signatures, or visual images) and converting them into an electrical signal that can be processed for decision-making (Chaudhari et al., 2024). Some popular examples are passive infrared (PIR) sensors, ultrasonic sensors, radars, thermal sensors, acoustic sensors, light detection and ranging (LiDAR), video-imaging, and magnetometers.

Occupancy Detection System

An outdoor occupancy detection system integrates one or more sensors with power, communications (e.g., D4i/DALI-2, Ethernet, BLE/mesh, cellular). And processing capabilities. Detection and classification may occur at the sensor or edge device, or with an external controller or cabinet (classification model runs in the system outside the sensor), depending on the system architecture. The resulting occupancy information can then be used to actuate luminaires or support other applications. Typical applications include smart street/area lighting, crosswalk beacons, curb management, and smart-city analytics.(Elkhokhi et al., 2025).

Contrast with Indoor Occupancy Detection Systems

Indoor systems operate in bounded, conditioned spaces with short ranges and relatively stable environmental conditions, whereas outdoor systems must contend with weather (rain, fog, snow), sun glare, longer standoff distances, and mixed road-user types. Outdoors, background dynamics such as wind-moved foliage, solar heating, headlight sweep, and temperature swings can further affect detection performance and false alarms (Kutilla et al., 2018).

Indoor occupancy systems typically integrate commodity sensors (PIR, vision, ultrasonic) with building gateways and cloud processing. Outdoor systems often require environmental hardening (e.g., IP-rated enclosures), rigid mounting, and alignment, and may shift processing to the edge for real-time actuation (e.g., lighting) without relying on continuous network connectivity. In public rights-of-way, privacy and policy constraints further shape modality choice including the use of radar, thermal sensing, or on-device processing instead of identity-resolving video (Fabrègue & Bogoni, 2023).

Taken together, these factors require a different design and evaluation approach for outdoor occupancy sensing. Sensor coverage must account for pole placement, lighting distribution, expected user paths, and environmental exposure, while sensor selection must consider robustness, response time, and privacy. Outdoor evaluations should therefore characterize sensor-level detection performance and spatial coverage under representative operating conditions rather

than relying only on end-to-end lighting-system behavior. Such evaluations are needed to understand how well different sensing approaches translate from nominal specifications to practical outdoor lighting applications.

SENSOR CAPABILITIES AND MARKET LANDSCAPE

For occupancy detection in smart street-lighting contexts, the literature and industry review identified seven prevalent sensing modalities: PIR, radar, LiDAR, acoustic, thermal imaging, video-based, and hybrid (multi-technology) sensors. The following subsections outline each technology's operating principles, typical variants, and outdoor characteristics, and summarize commercially available products.

Passive Infrared (PIR) Sensors

PIR Working Principle

PIR sensors use infrared sensitive pyroelectric sensing elements and optics (typically Fresnel lenses or mirrors) to sense changes in long-wave infrared (thermal) radiation as a warm target moves across discrete zones formed by optics. Motion across adjacent zones produces a differential signal while stationary targets are generally not detected once the thermal signal becomes stable (Mukhopadhyay et al., 2018; Rafique & Siddiqui, 2013; Yun & Lee, 2014).

PIR sensors for occupancy detection typically employ a single large-area photodiode. In some configurations, two or four photodiodes are connected in series or arranged differentially, allowing their responses to be compared to improve motion detection. Certain PIR devices may also incorporate a thermopile detector, where an optical system images each detection zone onto a portion of the thermopile array, enabling absolute temperature measurement in addition to motion sensing.

By design, the PIR sensor and its optical system integrate the incident infrared radiation across the surface of the sensing element. This means that the detector effectively measures the combined thermal signal of the entire field of view rather than isolating individual sources. To ensure selectivity, PIR sensors include an optical bandpass filter, typically restricting the response to the 8–13 μm wavelength range. Within this spectral band, infrared intensity corresponds to the thermal radiation of objects at temperatures approximately between $-40\text{ }^{\circ}\text{C}$ and $125\text{ }^{\circ}\text{C}$. Consequently, the electrical output of the detector is proportional to the apparent temperature of the visible scene.

There is a related class of sensor known as active infrared (AIR). AIR sensors operate on a fundamentally different principle, using an emitter–receiver pair (beam-break or retroreflective). These are commonly used in bollards and trail counters, performing well in constrained path environments. However, they offer limited classification capability and are generally unsuitable for complex environments such as busy intersections (Kothuri et al., 2017a; Shokrollahi et al., 2024).

PIR Types

- By Output Style
 - Binary modules: Provide simple presence/absence detection.
 - Analog/signal modules: Generate waveforms that can be post-processed to infer additional information such as direction of travel or approximate speed.
- By Sensing Element
 - Single vs. Dual Pyroelectric Elements: Dual configurations improve motion detection accuracy and reduce susceptibility to background fluctuations.
 - Thermopile Detectors: Measure absolute infrared radiation, enabling both motion detection and static temperature monitoring.
 - Pixelated Photodiode Arrays: Semiconductor-based arrays that provide low-resolution thermal imaging, supporting classification tasks such as distinguishing between pedestrians and cyclists.
- By Optics
 - Fresnel Lenses: Lightweight, low-cost optics that segment the field of view into multiple detection zones.
 - Mirror Optics: Offer more precise focusing and control of field-of-view geometry, though typically at higher cost.

PIR sensors can vary in both signal output and optical design. Binary modules provide a simple presence or motion output, while sensors exposing a processed or analog signal can support more advanced interpretation. Optical configurations are particularly important because Fresnel lenses or mirror optics define the number, orientation, and spatial distribution of the detection zones. Fresnel lenses are widely used because they provide lightweight and low-cost control of the detection pattern, while different lens geometries can produce substantially different coverage footprints.

PIR Detection Range and FOV

PIR coverage is governed primarily by the Fresnel-lens pattern and mounting geometry (height, tilt, offset), which partition the scene into discrete zones that must be crossed to trigger detection. Modeling and optics studies link lens design directly to zone spacing, angular sensitivity, and effective range; consequently, the optic and aim should be selected to match expected motion trajectories (e.g., corridor vs. open area) to avoid blind regions (Davis et al., 2022; Mukhopadhyay et al., 2018).

In general, corridor lenses concentrate detection zones along a narrow azimuth, extending reach along paths, whereas wide-angle lenses trade reach for broader coverage. Detection is also

geometry-dependent: lateral motion across detection zones is generally more readily detected than radial motion toward or away from the sensor. The band-pass filtering used in occupancy modules makes very slow motion under-responsive and very fast motion susceptible to late triggers. Reported fields of view in the literature span narrow patterns ($\sim 10^\circ \times 80^\circ$) for path monitoring to wide patterns ($\approx 90^\circ \times 90^\circ$) for general presence, illustrating the central role of optics in setting both range and footprint (Rafique & Siddiqui, 2013; Yun & Lee, 2014).

Because usable “range” depends on target–background thermal contrast (ΔT), motion speed/direction, and lens transmissivity, most protocols treat range and FOV as measured performance variables rather than fixed specifications; studies report short-to-mid-standoff human detection, with achievable distance increasing when ΔT is high and motion is predominantly lateral (Davis et al., 2022; Yun & Lee, 2014).

PIR Outdoor Behavior

Outdoors, PIR performance is constrained by reduced ΔT in hot weather and by background dynamics (wind-moved foliage, solar heating/cooling cycles, headlight sweep), all of which can elevate false alarms. these effects are repeatedly documented and motivate dual-technology designs (PIR + microwave) or fusion with other modalities at complex sites (Shokrollahi et al., 2024). Target emissivity and clothing also matter; heavily insulated pedestrians in winter and pedestrians on sun-warmed pavement in summer can be harder to distinguish from the background. For vehicles, detection depends on warmed components; cold-start vehicles in cool ambient conditions may present weak signatures for several minutes. A practical design consequence is that the sensor footprint rarely matches the lighting footprint at typical pole heights: luminaires often throw light two or more mounting heights, while PIR detection commonly extends closer to ≈ 1 mounting height, creating under-lit gaps unless zones are overlapped or networked to pre-emptively raise adjacent luminaires.

PIR State of Practice

For street/area-lighting, PIR is available as standalone pole-/wall-mounted modules for plug-and-play triggers and as luminaire-integrated nodes for street/area lights (Table 1). Typical range of PIR in streetlighting application is usually up to 30 m. Most products target slow-moving road users (pedestrians/bicycles). Some vendors claim bicycle vs pedestrian classification via PIR alone, but these claims are not supported by independent studies.

Table 1. Commercially available PIR sensors (industry scan excerpt)

Product	Integration	Object speed	Classification capability	FOV	Range	Mounting height	Cost	Other
Tvilight	Pole, plug-play	4-130 km/h	Cars, bicycles, pedestrians	$>270^\circ$	15m sides, 9m front, 3m back	5m		astronomical clock, remote management, false filter: birds, wind, rain, small animals

Panasonic Long Distance	Into fixture	3.6 km/hr	Cars, bicycles, pedestrians	180° x 99°	16m x 19m	7m	\$50 - \$100	high signal to noise ratio, low current (1, 2 or 6μA)
Panasonic Ultra-wide Long Distance	Into fixture	3.6 km/hr	Cars, bicycles, pedestrians	92° x 45°	12.6m X 31m	10m - 15m	\$50 - \$100	high sensitivity on the aisle entry and exit area, optimized for radial movement
Panasonic Specific Area	Into fixture	3.6 km/hr	Cars, bicycles, pedestrians	56° x 112°	12m, 6m, 3m		\$50 - \$100	pyroelectric infrared motion sensor
Lumawise	Into fixture	-	Cars, bicycles, pedestrians, wheelchairs		30mx6 m, Ø10m circular	5m	\$6052	fit into the Zhaga-D4i ecosystem
Avi-on Direct Connect PIR Sensor	Product specific controller	-	-	90°	12 m	2.5-12 m	\$50	Bi-level PIR, photocell, schedule, easy connect to Avi-on fixtures
Optex America	Pole, plug-play	1-7 km/hr	Pedestrians, animals	85°	2.5 - 12 m	2.5 to 3m	\$152	animal tolerance, area masking, cover modification
e-save	Product specific controller		Pedestrians	90°	17m x 17m	6m, 12m		Combined with an e-save SLC-Hub

Radar Sensors

Radar Working Principle

Radar sensors transmit electromagnetic energy (most commonly microwaves) and analyze the backscattered signal to infer the presence and motion of targets. For continuous-wave (CW) radars, the key observable is the Doppler frequency shift, which yields radial speed and enables motion-based occupancy detection. Frequency-modulated continuous-wave (FMCW) radars sweep frequency over time; by mixing the return with the transmit signal, they can recover range from the beat frequency and velocity from Doppler shift and, with antenna arrays, estimate target direction or angle of arrival through beamforming. Pulsed radars measure time-of-flight of short bursts to estimate range directly. Across these types, detectability depends on target radar cross section (RCS), wavelength, transmit power, antenna characteristics, receiver sensitivity and noise, and processing gain (Avotins et al., 2021; National Aeronautics and Space Administration, 2010; Polivka, 2007).

Radar Types

Three types of microwave radar sensors were reviewed. The capabilities of these radars vary with operating principle, carrier frequency, antenna configuration, sensitivity, signal processing, and radar cross-section of the target (Avotins et al., 2021).

- **Continuous wave radars:** (i) primarily measures target radial velocity, (ii) use a mixer to compare transmitted and received signals, (iii) use a separate transmitter and receiver antenna or circulator.

- **Frequency-modulated continuous-wave radars:** (i) measure both range and velocity, (ii) require controlled frequency control and calibration, and (iii) use the frequency difference between transmitted and received signals to estimate range.
- **Pulse radars:** (i) estimate range from the time delay between transmitted and received pulses and can estimate velocity from successive measurements, (ii) may use a duplexer to switch between transmitting and receiving.

Radar Detection Range and FOV

The detection range of radar sensors is primarily driven by radar equation including transmitted power, antenna gain, target radar cross section, wavelength, receiver sensitivity, and processing gain and received signal strength falls with the fourth power of distance. The field of view is primarily determined by the antenna beamwidth. Narrow beams increase gain and range but reduce coverage; wider beams increase coverage but reduce range and angular resolution (Park et al., 2024). Mounting geometry (height/tilt), occluders, and clutter also shape the effective footprint. Compared with PIR, radar sensors are effective at detecting motion over larger distances and provide velocity cues, but radar systems are generally more expensive and draw more power.

Radar Outdoor Behavior

Outdoors, radar often benefits from line-of-sight but can remain effective under partial occlusion and in low-visibility conditions where optical sensors degrade. Propagation through rain, fog, or snow is markedly more resilient than visible/IR imaging, attenuation rises with frequency and precipitation rate, but mmWave bands typically retain useful performance in weather that severely impacts cameras/LiDAR (National Aeronautics and Space Administration, 2010; Rouveure et al., 2018). While radars may still be effected by various weather conditions, they generally are able to outperform other sensors in these conditions (Guobadia, 2024). Background clutter (foliage motion, rotating fans) and multipath can raise false alarms if not filtered, while human micro-Doppler signatures and track consistency help disambiguate targets. Practical implications: use antenna patterns and zone masks to bound the scene; align beam orientation with expected approach vectors; and tune update cadence (CPI/frame time) to balance responsiveness and noise.

Radar State of Practice

A review of the industry revealed multiple radar -based sensors commercially available for the purpose of integration into roadway lighting systems. These radars are typically advertised to detect a variety of objects including pedestrians, cyclists, motorcycles, cars, and trucks. The radars range can vastly vary based on the technology used, ranging from 15 to 400 meters within the reviewed products.

Table 2. Commercially available radars (industry scan excerpt)

Product	Integration	Object Detection	Classifications Capability	FOV	Range	Mounting Height	Control	Cost	Other
Avi-on's Outdoor Long Range (Avi-on, 2025)	Standalone	moving	-	360°	30 m X 75 m	12 m	0-10V dimming	-	Mesh Radio Freq: 2.4GHz Wireless Standard: BLE 4.2 with Avi-on Mesh Point to Point Range*: 80ft with obstructions and 350ft unobstructed
Robus 360° Radar Surface-Mounted Sensor (Robus, 2023)	Standalone	moving	-	360°	Ø20 m circular	4-15 m	0-10V dimming	\$108	With 3 Step Dimming
ClairWav-T24L (Dymec, 2025)	Standalone	moving	-	-	400 m	5-8 m	-	-	Installed at the center of the road, multi-lane, high-precision detection
E-save Light Radar (Esave, 2019)	Plug-play	moving	pedestrians, cyclists, motorcycles, cars, and trucks	34° x 80°	20 m	~ 3 m (Assumed)	-	\$400	Speed and direction capability
Philips Outdoor Multi-sensor (Philips, 2021)	Stand-alone/ plug-play	max 145 km/hr	pedestrians, cyclists, motorcycles, cars, and trucks	180	15 m pedestrian s, 30 m cars	4-12 m	DALI-2, D4i	-	Bluetooth Mesh 2.4 GHz
Livable Cities (Liveable Cities, n.d.)	Plug-play	5 – 200 km/hr	Vehicle	-	40 m	8.5 m	0-10V, DALI	\$500	Optional integration with video detection
SmartWalk 1400 (Marlin Controls Inc., n.d.)	Plug-play	-	Pedestrian	Adjustable	-	Above 3 m (Assumed)	Analog signal	\$1416	Ideal for crosswalk pedestrian detection

Light Detection and Ranging (LiDAR)

LiDAR Working Principle

LiDAR utilizes the principle of Time of Flight (TOF). TOF describes the time taken for a beam of near-infrared radiation to be reflected around an area and return a signal to an integral charge-coupled device (CCD) sensor. If the TOF is continuously changing, the assumption is that an individual or vehicle is present and moving. Multiple beams can be emitted, and the returned near infrared (NIR) signal is analyzed to identify the size, speed, and direction of travel of an object or person (Nazmuz, 2022).

This technology makes use of shorter electromagnetic waves than microwave radars, allowing it to have better angular resolution. However, the smaller wavelengths come at a cost of reduced penetration of various weather conditions.

LiDAR Sensor Types

- Mechanical LiDAR's: Uses rotating or oscillating optical components (e.g., mirrors or prisms) to scan the environment, typically providing a wide field of view (upto 360°) and long detection distances (Lopac et al., 2022)
- Solid-State LiDAR: Has no large moving parts and uses electronic or optical beam steering. It is generally more compact, but field of view, rang and resolution vary depending on the specific design (e.g., multiple sensors design) (Lopac et al., 2022).

LiDAR Detection Range and FOV

A LiDAR's range and field of view can be altered by multiple aspects of technology. As previously mentioned, a mechanical LiDAR can achieve a field of view of 360 degrees by rotating the sensor through the use of mechanical components. However, solid-state LiDAR's do not have the ability to rotate these sensors, so their field of view is driven by other components like additional sensors, beam steering technology, and optical components such as wide lenses (Lin et al., 2022; Lopac et al., 2022). The range of these sensors is generally influenced by the power and wavelength of the laser as well as the beam divergence (Dai et al., 2022).

LiDAR sensing depends on the line-of-sight, its “view angle” or “capture angle” and may exhibit a blind spot near to the pole. Near objects can shade and hinder the detection of far objects. If the sensors are mounted too high, the emitted beam may not be able to sweep across areas near the pole where an individual or vehicle is located.

LiDAR Outdoor Behavior

Outdoor LiDAR performance is influenced by atmospheric visibility and weather because both the transmitted and reflected optical signals travel through the surrounding air. Rain, fog, snow, and airborne dust can scatter or attenuate the laser signal, reducing the strength of returns from the intended target and decreasing effective detection range. (Heinzler et al., 2020; Naich & Carrión, 2024).

Atmospheric particles can also return a portion of the emitted light directly to the sensor, producing spurious range measurements or additional points that do not correspond to the intended road user or object. In scanning systems, these effects can introduce noise into the measured spatial data and can contribute to both missed targets and unwanted detections.

With LiDAR, no clear camera-like image is captured, but the system can determine the outline and size of the moving object or individual, thereby avoiding privacy issues.

LiDAR State of Practice

Most commercially available LiDAR's are advertised at a relatively high detection range and field of view. On top of this, many LiDAR's have expectational capabilities in detecting vehicles, pedestrians, and bicycles, though this technology generally tends to be sold at a higher price when compared with other sensing technologies.

Table 3. Commercially available LiDARs (industry scan excerpt)

Product	Vertical FOV	Range	Laser Wavelength	Interface	Object Classification	Cost
Ouster (Ouster, 2025)	H: 360; V: 22.5° - 180°	0.5 – 200 m	865 nm	Omnisight	Vehicle, Bicycle, Pedestrian	~\$6,999
Seyond (Seyond, n.d.)	H: 360; V: 120°	1.5 -250 m	1550 nm	D2, Seyond	Vehicle, Bicycle, Pedestrian	~\$6,300–\$11,196
Sick (Sick Sensor Intelligence, 2025)	H: 360; V: 1 - 270°	8 m	850 nm	Ethernet, USB. PNP	NA	\$2,840.90–\$2,856
Hokuyo (Sentek Solutions, n.d.)	H: 360; V: 270	30 m	905 nm	Ethernet, USB. PNP		\$2550–\$4300
Quanergy (Quanergy, 2025)	90°	140 m (70 m radius range)	905 nm	Windows 10/11	Pedestrian, vehicle, bicycle	\$6200–\$12800

Acoustic Sensors

Acoustic Sensors Working Principle

Two related modalities fall under acoustic sensing for outdoor occupancy:

- Active ultrasonic (sonar): it emits high-frequency sound (typically ~40 KHz) and measures echoes or Doppler shift to infer the presence and motion of nearby objects. Because sound diffracts around small objects, ultrasonic can detect motions even with partial occlusion, but useful range is generally short and degrades in rain and wind (PNNL, 2019).
- Passive acoustic (microphones/arrays): It does not emit sound: it captures ambient audio and uses features (spectral/temporal) and beamforming to detect, localize and classify road users. Arrays can steer “listening beams”, enabling direction of arrival and with multiple sensors, localization- even for out of sight events (Izquierdo et al., 2021; Schulz et al., 2021).

Acoustic Sensor Types

- Ultrasonic: (i) Doppler motion sensors (presence via frequency shift), (ii) time-of-flight rangefinders (echo timing), and (iii) multi-transducer arrays for limited shaping of the acoustic beam (PNNL, 2019)
- Passive acoustic: (i) single-mic, (ii) microphone arrays with beamforming (localization and tracking). (iii) acoustic cameras (array + visual overlay) used for classification and source mapping (Staines et al., 2022; Verreycken et al., 2018).

Acoustic Sensors Detection Range and FOV

The range of active ultrasonic (sonar) is usually short ($\sim 0.2 - 1$ m) and depends on transducer frequency (typically ~ 40 kHz), output power, and beam pattern (typically conical, $\sim 10-60^\circ$). FOV of passive-acoustic sensor is determined by array aperture and beamforming. Larger array spacing and more elements improve direction-of-arrival accuracy and standoff distance. Coverage is typically tens of meters for vehicles (engine/ tire signatures) and shorter for pedestrians, depending on ambient noise and processing (Chakravarthula et al., 2023).

Acoustic Sensors Outdoor Behavior

Wind introduces broadband noise and fluctuating pressure, degrading SNR for microphones and causing false Doppler on ultrasonics; rain can create spurious echoes for sonar and masking noise for microphones. Foam windscreens, mechanical baffles, and wind-robust filtering are often required. Traffic, construction, and fauna elevate false positives/negatives—especially for pedestrian detection with passive audio. Narrow-band features (e.g., engine harmonics, tire-road spectra) remain reliable for vehicles; crowd noise is more challenging.

Hard ground or facades produce multipath; soft vegetation absorbs high-frequency ultrasound, reducing range. Careful placement (height, standoff, tilt) and exclusion zones help mitigate multipath and fluttering foliage.

Outdoor deployments typically avoid raw audio retention; on-edge feature extraction or event flags (presence/class) are preferred to meet privacy expectations.

Acoustic Sensors State of Practice

Most off-the-shelf outdoor acoustic sensors found in the industry scan (Table 4), are ultrasonic rangefinders originally built for level/object measurement. Manufacturers also list people/object detection as an additional use case, but practically these behave as narrow-cone, point sensors: best for presence/triggering on a lane, path, driveway, or doorway- not for wide-area coverage or fine classification. Spec sheets commonly note that detection range depends on the object's reflection properties, size, and alignment; in practice, small or soft/absorbent targets (e.g., a person in loose clothing) at oblique angles return weaker echoes than large, hard, on-axis surfaces (e.g., a vehicle body or flat plate).

Table 4. Commercially available acoustic sensors (industry scan excerpt)

Product	Integration	Classification	Range	Operating temperature	Cost	Other
Tough Sonic (Senix, 2020)Joseph Vlasits	Stand-alone	Natural Objects	10 - 15.2 m	-40 to 70 °C	\$618	Tank level, long range object detection.
HRXL-Max Sonar (MaxBotix)	Stand-alone	Natural Objects	10 m	-40 to 65 °C	\$125	Tank level, long range object detection, proximity zone, robot ranging.
SICK (SICK, n.d.)	Stand-alone	Natural Objects	8 m	-25 to 70 °C	\$580	Detection range dependent on reflection properties, size, and alignment of the object.

Thermal Imaging Sensors

Thermal Imaging Working Principle

Thermal imaging sensors differentiate themselves from PIR sensors by creating a spatial thermal representation of a scene based on long-wavelength infrared radiation that is emitted by objects and converting it into processible data (Wilson et al., 2023). This thermal image is created through the use of an optical lens that focuses the infrared radiation into an infrared detector (Chandler, 2013). These infrared detectors are able to perceive detect subtle changes in temperature ranging from $\sim -20^{\circ}$ to $2,000^{\circ}$ Celsius depending upon the technology used within the sensor. The data collected from the infrared detector is then processed and used to create a thermogram representing spatial variations in thermal radiation. Detection and tracking algorithms can use this information to identify road users within a configured area.

Unlike conventional PIR sensing, which responds primarily to changes in infrared radiation across discrete optical zones, thermal imaging retains spatial information within the scene. This allows thermal systems to evaluate target shape, position, movement, and persistence across successive frames and can support more advanced detection or classification than a binary PIR output.

Thermal Imaging Types

Infrared imaging technologies can be categorized by the spectral band in which the detector operates. Common bands include:

- Long-wave infrared (LWIR): $8 - 14 \mu\text{m}$
- Mid-wave infrared (MWIR): $3\mu\text{m}$ to $5\mu\text{m}$

- Short-wave infrared (SWIR): 0.9 – 1.7 μm

The choice of spectral band affects atmospheric transmission, detector technology, sensitivity to emitted versus reflected radiation, system cost, and suitability for different sensing applications. LWIR is commonly used for uncooled thermal imaging and pedestrian-presence applications because objects near typical outdoor temperatures emit strongly within this region.

Thermal Imaging Detection Range and FOV

A thermal imaging sensor's detection range is mainly determined by the lens aperture and focal length of the sensor (Perić et al., 2019). However, the range of these sensors can also be highly dependent based on the ambient temperature and relative humidity they are exposed to. These conditions affect the range of thermal imaging sensors due to water molecules in the air between the sensor and the objects, impacting the amount of IR radiation that the sensor is able to absorb. Conditions with higher absolute humidity may require the use of mid-wave IR sensors that are capable of a higher range detection when water molecules decrease the range of detection for long-wave IR sensors (Khare et al., 2018). The field of view of thermal imaging sensors is primarily driven by the size of the sensor and the focal length. A wider field of view generally increases the size, weight and cost that is associated with the sensors (Wirth-Singh et al., 2023).

Thermal Imaging Outdoor Behavior

When mounted outdoors, these sensors excel in reducing false detections from environmental clutter, such as trees or inanimate objects, as their heat signatures do not impact the detection of road users. However these sensors have issues when extreme temperatures impact the environment and cause the temperature difference between the background and targets to decrease (Tumas et al., 2020; Wilson et al., 2023). As previously mentioned, temperature and humidity also impact the performance of these sensors when they are mounted in outdoor environments and can also drive the selection of the sensor type when mounting thermal imaging sensors in areas with higher absolute humidity, as it was found that mid-wave IR sensors perform better in penetrating higher amounts of water molecules within the air (Khare et al., 2018).

Thermal Imaging State of Practice

A scan of the industry revealed various thermal imaging sensors that are readily available for the application of road user detection. These sensors typically have a moderate range and the ability to detect different types of road users including pedestrians, bicycles, motorcycles, and trucks.

Table 5. Commercially available thermal imaging sensors (industry scan excerpt)

Product	Classification Capability	FOV	Range	Cost	Other
TrafiSense AI (FLIR) (Teledyne Flir, n.d.)	Bicycle, Pedestrian	90°H x 69°V, 32°H x 26°V,	Vehicle: 0 to 54m, 19.8 to 121.9 m.	~ \$4825	Conditional presence detection by class. Traffic Data Collection incl. conditional turning movement counts, Queue Length, Monitoring PSH (Position, Speed and Heading)

					over API - optional license, Wrong Way Driver Detection - optional license
Hanwha Vision TNO-L4040T (Hanwha Vision, 2024)	-	H: 32° / V: 24.3° / D: 39.2°	Minimum 11m	\$4423	Uncooled microbolometer. Directional detection, Loitering, Tampering, Virtual line, Audio detection, Temperature detection, Sound classification, Shock detection.
Axis Q1951-E Thermal (AXIS Communications, 2022)	-	H: 10° - 55°	1.3m – 33m	\$ 4339	Pure thermal stream with on- edge analytics options; robust enclosure.
Avigilon H4 Thermal (Avigilon, 2021)	Pedestrian, vehicle	45.9° x 36.5°	310 m	\$4828	Thermal camera with self- learning video analytics
Teledyne FLIR TrafiOne (195 / 156)	Pedestrian, vehicle	HFOV 95° or 56°	Stop-bar vehicle/bike: upto 25 m; Ped/Bike upto 20 m	\$2,000	Ped/bike presence, stop-bar detection, queue/travel time via Wi-Fi

Video-Based Detection

Video-Based Detection Working Principle

In video-based detection, a camera is utilized to capture images within a perimeter, then an image-based processing software analyses changes within individual rectangles found within the image and changes within the environment are detected. Subsequent images can be automatically compared to identify these changes, which may be related to object movement of a minimum size, rather than heat movement. (Alva et al., 2012). This process is done passively and does not require the camera to actively emit any signals such as microwaves or laser. A video-based detection system consists of a camera, microprocessor-based computer for digitizing and processing the imagery, and software for interpreting the images (Mimbela, 2007). These systems capture imagery and may therefore require consideration of privacy and data-management practices, particularly when images are stored or can be used to identify individuals.

Video-Based Detection Types

- RGB Cameras: A color filter array is utilized to capture red, blue, and green to create colored images.
- Monochrome Cameras: Lack of a color filter array to focus on absorbing more light for higher quality images.

- **Low-Light Cameras:** low light cameras utilize either charge integration or electron multiplication in order to have an increased exposure to increase the cameras functionality in dark environments (GlobalSpec, n.d.).

Video-Based Detection Range and FOV

The detection range for video-based sensors can be based both on the hardware and mounting of the sensor. A higher mounting allows the sensor to see over larger vehicles and environmental geometry, increasing the maximum range. Other environmental elements such as inclement weather will also limit the range of these cameras (Mimbela, 2007). A camera's lens also plays a vital role in the detection distance of these sensors. Cameras with short focal lengths provide wider fields of view, while cameras with longer focal lengths typically have a smaller field of view.

Video-Based Detection Outdoor Behavior

Video-based sensor technology faces detection issues when the sensor is mounted in an outdoor environment. The main problem video-based sensors are presented with when mounted outdoors are inclement weather conditions and low light levels which may impact the visibility of these sensors. Low light conditions at night, shadows cast onto the roadway, and debris occluding the lens can create a problematic environment for video based sensors to operate that are reliant on the ability to process clear images (Mimbela, 2007).

One option is to use NIR emissions, but that introduces the concern about insufficiently studied NIR light pollution. Another approach is image processing algorithms and/or different lenses designed for lowlight conditions. Some cameras are able to see more clearly in dark environments by using a combination of RGB and monochrome cameras that provide a brighter and more clear image (Zhao & Lam, 2024). Other low light cameras are also specifically designed to function in dark conditions (GlobalSpec, n.d.). Various other environmental factors, like foliage, may also cause obstructions and false detections when these elements are within the view of the camera, but algorithms are trained to ignore these objects and reduce false detections when possible (Kolluri & Das, 2023).

With video-based detection systems, privacy has been a major issue, but the resolution can be intentionally filtered so that faces are not identifiable, nor mineable after the fact for private information. Edge-computing Artificial Intelligence (AI) apps are already in use to remove the identification data from the photos. The potential is high for camera-based systems to detect object motion over larger distances when compared to PIR. In addition, it has promise to match the detection pattern with the light distribution pattern.

Video-Based Detection: State of Practice

An initial scan of the industry revealed multiple products aimed at using video sensing technology for road user detection. The pricing, detection range, and FOV of these sensors can vary greatly depending upon the specifications of the cameras.

Table 6. Commercially available video-based sensors (industry scan excerpt)

Product	Classification Capability	FOV	Range	Cost	Other
ClairWav-T24C (Oymec American Industrial, n.d.)	vehicles	90°	400 m	-	Detection of up to 256 traffic objects at once
Autoscope Vision (Econolite, 2024)	Pedestrians, cyclists, motorcycles, cars, and trucks	185 m	-	~\$6915 (system)	Stop-bar through and left turn, High-Definition (HD) camera for superior video images, Pedestrian crosswalk
VersiCam Iteris (Iteris, 2024)	-	4.6° to 46.0° (FOV horizontal)	-	~\$6200 (system)	VersiCam Wireless” package (camera + ICC-2W, antennas, cabling)
SCW Deputy 4.0 v5 (SCW, 2025c)	Pedestrians	124° (horizontal)	35 m	\$275	Detects at 115 ft., recognizes faces at 50 ft, identify faces at 35 ft; Wide dynamic range; has night vision
SCW Warrior 4.0 v5 (SCW, 2025e)	Pedestrians	89°(horizontal)	45.72 m	\$275	Detects at 150 ft, recognizes face at 75 ft, identifies face at 50ft; has night vision; can create inclusion and exclusion areas for the motion tracking; can record in H.265
SCW Bastion 4.0 (SCW, 2025a)	Pedestrians, vehicles	varifocal: 50.85° to 3.47°	173.736 m	\$740	-
SCW Lookout Mini 5.0 v2 (SCW, 2025d)	Pedestrians, vehicles	varifocal: 107.6° to 30.6°	60.96 m	\$625	-
SCW Beacon 8.0 (SCW, 2025b)	Pedestrians, vehicles	58.4° to -2.08°	~3218.68 m	\$2980	-

Hybrid Sensors

Hybrid Sensors Working Principle

Hybrid nodes combine two (or more) sensing modalities and improve detection/classification under varied conditions. The sensing modalities commonly combined within hybrid sensors are radar + video, thermal + video or Wi-Fi (travel-time), or PIR + microwave to reduce single-sensor failure modes (e.g., video glare, radar occlusion). Radar–camera and thermal–visible fusion consistently show gains in robustness and tracking, provided calibration and synchronization are done correctly (Lee et al., 2015).

Hybrid Sensor Types

- Radar + Video (single housing): deep-learning fusion of a 61 GHz radar with an RGB camera yields person/vehicle tracks and events.
- Thermal + Wi-Fi (with optional HD video): thermal imaging provides VRU/vehicle presence day–night and in glare; Wi-Fi adds anonymous travel-time/queue metrics.

- Radar + Video (cabinet platform): intersection-grade fusion with long standoff and lane zoning (e.g., Iteris Vantage Vector/Next, Vantage Apex).
- PIR + Microwave (dual tech): security-grade outdoor detectors used as reliable presence triggers.

Hybrid Sensors Detection Range, FOV, and State of Practice

In commercially available hybrid nodes that fuse Wave radar with RGB video, typically a wide horizontal FOV is around a right angle ($\approx 90\text{--}100^\circ$) from the radar, while the camera's HFOV can be set wider or tighter via lens. In “area” use, person detection is generally effective from roughly 5–60 m and vehicles from 5–90 m; with a road-profile tuned for long standoff, vehicle detection can extend to about 150 m. Cabinet-style intersection platforms built around the same fusion concept advertise advance detection out to 183 m lane-by-lane. Mounting height is usually $\sim 3.5\text{--}12$ m, with range/FOV tuned by tilt and zone configuration.

Thermal-centric hybrids for crosswalks and approaches use wide lenses (e.g., $\sim 56\text{--}95^\circ$ HFOV) and are normally mounted at $\sim 3.5\text{--}8$ m. They're optimized for presence in short-to-mid ranges, 0–25 m to the stop bar or crossing and maintain detection in darkness and glare; the Wi-Fi module contributes travel-time and queue metrics. Higher-end thermal units with multiple lens options can cover short-range presence while also monitoring farther out (up to ~ 150 m, lens-dependent) when approach awareness is needed. These systems provide both relay (dry contact) and network (IP) event outputs, allowing dimming to be activated either by a direct hard-wired trigger or via lighting controller that reacts to IP events. PIR + microwave “dual-tech” triggers are short-range, wide-coverage presence sensors, typically ≤ 15 m with $\sim 90\text{--}120^\circ$ patterns and are best used as reliable bollard/sidewalk triggers rather than long-standoff detectors.

Hybrid Sensors Outdoor Behavior

Under adverse weather and challenging illumination, different modalities fail in different ways; LiDAR performance degrade with suspended particles (fog, rain, snow) due to backscatter and attenuation (Dreissig et al., 2023; Kim et al., 2023), while RGB video is vulnerable to glare and strong light. By contrast, microwave sensing is comparatively robust to both, and thermal maintains target contrast in darkness and through headlight glare. Multi-sensor fusion exploits these complementary failure modes to reduce missed detection and false alarms across conditions. Representative experiments document LiDAR degradation in rain/fog and motivate fusion with radar/camera; thermal-infrared work highlights robustness to illumination at night (Lee et al., 2015; Rivera Velázquez et al., 2022).

Table 7. Commercially available hybrid sensors (industry scan excerpt)

Model	Modalities fused	FOV	Range	Mounting height	Interfaces	Typical use case / Notes	Cost
Teledyne FLIR ThermiCam	Thermal + (optional Wi-Fi)	90×69 (veh presence 0–25 m, 5–60 m)	distance varies with FOV: 0–	Intersection pole; height per lens FOV	1×N/O + 1×N/C dry contacts; 16 via TI	Thermal AI presence & classification; turning	\$4,343

AI (690 / 645 / 632)	travel-time) + Edge AI	monitoring); 45×37 (10–100 m); 32×26 (15–150 m)	25 m,10–100 m, 15–150 m		BPL3; APIs; PoE; BPL; Wi-Fi	counts; travel time	
Axis Q1656-DLE	Radar + Video	95° radar field	person 5–60 m, vehicle 5–90 m in area profile, road profile up to 150 m	3.5–12 m	PoE or 10–28 VDC	all-in-one fusion for area/lane occupancy	\$2,917
Iteris Vantage Apex	Radar + Video		Upto 180m	2.1–2.7 m			\$3,000
Bosch OD850 TriTech	PIR + Microwave		15 m×15 m			Ideal as a short-range outdoor trigger.	\$248

RESEARCH EVALUATIONS OF SENSOR CAPABILITIES

As part of this literature review, an analysis of other studies was conducted that performed tests on sensors or lighting systems with integrated sensors (Table 8). These studies showed multiple environments that sensors have been tested in from labs to real world deployments. It was shown through some of these studies that elements of the environment, like temperature and weather, can have impacts on the performance of some sensors (Juntunen et al., 2018; Kothuri et al., 2017b; Mohring et al., 2018). Other elements related to the specifics of how the sensors were mounted also drove how well the sensor functioned within the environment, and the amount of false detections that occur (Avotins et al., 2021; Guobadia, 2024; Juntunen et al., 2018) When it came to the detection the detections of road users, many of these sensors did well in lower traffic volumes. However when more complex scenes with a higher amount of vehicle or foot traffic were introduced into the sensors field of view, some issues began to arise as it created difficulties in determining the amount of traffic or specific type of road user (Kothuri et al., 2017b; Mohring, 2018; Nguyen et al., 2014).

Table 8. Summary of Sensor Evaluation Studies

Study	Evaluated Sensors	Test Environment	Methods	Results
(Avotins et al., 2021)	Microwave Radar, Long-range PIR, Short-range PIR	Lab	Sensors were mounted in a window aimed at roadway. Readings were compared to vehicle speed and direction.	Radar accurate within 30 m; accuracy improved when angled 22° vs perpendicular, showing mounting angle critical.
(Mohring, 2018)	PIR, Sonar (UVD), Lidar	Real world deployment	Sensors mounted on active luminaire; exposed to weather; validated with camera/weather sensor.	PIR is most suitable for adaptive lighting: 92% active traffic accuracy but only ~73% counting accuracy.
(Guobadia, 2024)	Ultrasonic, PIR, Laser sensors, Radar	Controlled parking lot	Vehicles/pedestrians moved within sensor range; logged timestamps; tested in fog/rain.	Ultrasonic gave false detections (noise). Laser required precise alignment; misaligned reduced accuracy.

(Mohring et al., 2018)	PIR, LiDAR, Thermographic, sensor	Live road and controlled road	Live and controlled tests: 600 vehicles, 600 peds, 400 bicycles; varied speed, density, direction.	PIR is best for detecting road users but weak at counting/classifying. LiDAR accurate for vehicles, weaker for peds/bikes. Thermographic accurate except with cold objects.
(UC Davis California Lighting Technology Center & HNEL, 2021)	Dual-tech, PIR+microwave, Solid-state LiDAR, Mechanical LiDAR, Mechanical LiDAR (smaller form factor)	Outdoor pole mounts, 4 ft AFG, sensors aimed horizontally; targets: pedestrians & vehicles	Sensors aimed horizontally; targets: pedestrians & vehicles, 48 detection tests per sensor; compared detection perimeter/pattern vs manufacturer diagrams.	PIR+MW: erratic perimeter; 15% failures. Solid-state LiDAR: 15% failures. Mechanical LiDARs (3 & 4): regular patterns; 0% failures. Narrow horizontal pulse missed targets <4 ft tall (children/pets).
(Juntunen et al., 2018)	PIR	Controlled environment and Real-world deployment	Controlled walking/standing tests; then 28 poles in adaptive lighting system with 3 PIRs each.	Performed well, but cold temps and wind caused false detections; lower mounting may reduce branch-induced errors.
NGLS – VTTI Parking Lots (2019)	PIR	Living-lab retrofit	6 parking lots, 58 luminaires; 30 ft mounts; observed response & troubleshooting.	None of the systems found reliable. Recurrent issues: sensitivity at 30 ft, directionality (transverse > radial), latency from central control (~1–3 s round-trip), low ΔT pedestrian/background, coverage mismatch (photometric > detection area), and unexplained misses even at 10–12 ft wall mounts. Detection footprints were much smaller than lighting footprints.
(Nguyen et al., 2014)	Microwave motion sensor	Controlled road	100 laps by cars, buses, trucks at different speeds.	80% accuracy for vehicle type and speed. Struggled with vehicles traveling consecutively
(Gagliardi et al., 2020)	Smart Camera (as part of a system review)	Real world pilot sites	Installed on poles at real-world sites.	Effective for traffic analysis and adaptive lighting/energy savings.
(Kothuri et al., 2017b)	Inductive loops, Thermal cameras, PIR, Pedestrian Signal Actuations	Controlled parking lot and real-world intersection	The study used inductive loops and thermal cameras to count bicycles, and pedestrian actuations with PIR to count pedestrians. Sensors were first tested in the lab, then deployed in the field. Bicycle tests involved two riding directions at 60 °F, followed by mixed traffic tests at 80–90 °F. Data from a real-world intersection was validated using cameras.	Thermal camera: 99% accurate for bikes, dropped to ~80% with side-by-side riders. PIR overcounted peds (~4%) due to vehicles protruding.
(Graeber et al., 2013)	PIR (Wattstopper FS-305) embedded in luminaire	Roadway; 28 ft AFG; temperate climate	Evaluated detection confidence vs distance for peds, bicycles, motorcycles, autos	Detection 100% only when close to pole; confidence dropped <35% beyond 12 ft in one direction and <10% beyond 12 ft in the other ($\approx <0.5\times$ mounting height). Detection 100% only when close to pole; confidence dropped <35% beyond 12 ft in one direction and <10% beyond 12 ft in the other ($\approx <0.5\times$ mounting height).
(Kinzey et al., 2012)	PIR	Parking lots	Retail plaza ($\approx 151,000$ ft ²) and office-park lot; mounting heights 22 ft and 33 ft AFG. Field observations of sensor behavior, inspection of hardware condition, aiming, and settings (time delay, minimum output).	Effective sensor coverage only ~30% of lot ($\approx 45,000$ ft ²), leaving large dead zones. Problems: physical deterioration of exterior sensors, insufficient PIR sensitivity at high mounts, inconsistent settings, false trips (aiming errors, wind, temperature differentials). Conclusion: concept supported, but sensor design, placement, and commissioning need significant improvement.

MARKET TRENDS

PIR sensors dominate the market due to their low cost, and simple integration, and have the largest market share. Recent market overviews explicitly note PIR as the leading technology segment by share, with microwave/radar growing fastest, which tracks what specifiers report in the field (Fortune Business Insights, 2024).

Radar, LiDAR, and Hybrid sensors are increasingly preferred for public transport hubs, infrastructure, large-scale parking, and smarty city deployments driven by IoT and energy management initiatives (Davis et al., 2022; 360iResearch™, 2025).

Where preferences are converging by application:

- Parking lots & area lighting: Cost-sensitive retrofits still deploy PIR (especially where pole spacing is tight), but sites seeking wider, earlier detection increasingly specify mmWave radar or radar+video to gain range, angle, and speed vectors under rain/fog—often with on-edge analytics.
- Crosswalks & approaches: Thermal is widely used for VRU detection at crossings because it maintains contrast at night and in glare.
- Intersections / curbside (traffic-adjacent): Thermal and radar (and their fusion with visible video) are popular because they operate across day/night and adverse weather, with literature showing RGB+LWIR or radar-vision fusion outperforming single-modality approaches (Gallagher & Oughton, 2023).
- Trails, campus paths, low-speed corridors: Active IR “bollard” beams and PIR counters remain common for narrow FOV triggers and counting—simple, low-cost, and targeted.

Standards & integration are shaping purchases. A major near-term driver is Zhaga-D4i (Book 18) and the broader DALI–Zhaga–TALQ alignment (EdisonReport Media Network, 2024) which makes it easier to plug radar, thermal, PIR, and hybrid nodes into streetlights via standardized sockets/data models. That interoperability lowers switching costs and encourages multi-sensor “swap-ins” as needs evolve.

Trajectory over the next few years shows privacy-preserving sensing in public rights-of-way will be default and more hybrid/fusion endpoints (e.g., radar-video, thermal-video) with on-edge AI for classification and tracking will be used.

GAPS IN RESEARCH

These gaps collectively explain why outdoor occupancy sensing results remain inconsistent across sites and products, and they motivate standardized, sensor-centric performance evaluation.

- Few standardized, open datasets were found for VRU/vehicle detection that span across outdoor environments, and variation in infrastructure geometry (mounting height and pole spacing).
- Much of the rigorous evaluation remains indoor-centric; outdoor studies are commonly systems-level rather than sensor-focused.
- No agreed framework was found for testing or documenting exterior sensor performance (scenarios, mount geometry, metrics).
- Mixed reporting of sensor-only versus system latency obscures where delays originate.
- Limited independent curves linking detection range/FOV to height/tilt for each modality.
- Sparse multi-season field studies on temperature-contrast drift (PIR/thermal).

- Weather effects (rain/fog/snow, wind-driven backgrounds) are often anecdotal; controlled cross-modal comparisons are rare.
- Limited empirical evaluations showing how thermal/radar (or on-edge redaction for cameras) align with policy requirements and user acceptance in public rights-of-way.
- Throughout the research, multiple studies were reviewed that analyzed different sensor capabilities and sensors used within smart roadway lighting systems. Most of these studies consisted of the review of how different sensing technology compared against one another, but no studies were reviewed in which different sensor types within the same category were compared (e.g., Mechanical vs Solid-state LiDAR).
- Few of the reviewed studies explicitly link measured detection performance to lighting outcomes; for example, how latency affects perceived safety or how detection range and field of view influence the avoidance of unlit areas.

RESEARCH QUESTIONS

The literature review identified several factors that may influence outdoor occupancy-sensor performance, including sensing technology and configuration, road-user characteristics, mounting geometry, movement relative to the sensing pattern, and environmental conditions. It also identified a need to relate sensor detection range and coverage to the requirements of outdoor lighting applications. Based on these gaps, this study focused on sensor-level detection range, spatial coverage, and detection rate under controlled nighttime outdoor conditions.

The study addressed the following research questions:

1. How did detection range, spatial coverage, and detection rate vary among the tested sensor configurations and, where applicable, across mounting heights?
2. How did detection rate vary among the road-user types evaluated in the study, and did these differences vary by sensor configuration?
3. How did sensor orientation and observed ambient and pavement-surface temperatures relate to detection performance across the tested sensor configurations?
4. What practical considerations do the measured detection range, coverage, and detection rate provide for selecting, placing, and configuring occupancy sensors for street and area-lighting applications?

The study did not directly evaluate false-positive rates, sensor or system latency, road-user classification accuracy, controlled adverse-weather effects, or resulting lighting energy savings. These factors remain relevant to complete adaptive-lighting-system performance but were outside the scope of the present sensor-level evaluation.

METHODS

Testing was conducted at night on a marked outdoor grid, with sensors mounted on a portable pole at prescribed heights and orientations. Pedestrians, bicyclists, wheelchair users, and vehicles traveled along fixed paths while sensor outputs and target positions were recorded. Detection range, spatial coverage, and detection rate were evaluated under different sensor configurations, road-user conditions, mounting conditions, and recorded environmental conditions. The following sections describe the technology-selection criteria, selected sensors, sensor test configurations and mounting, experimental design, test facility and equipment, data collection procedures, and data analysis.

TECHNOLOGY SELECTION CRITERIA

Technology Selection Criteria

Sensors were selected to represent commercially available technologies suitable for outdoor street and area-lighting applications. Candidate technologies and products identified through literature and industry review were screened using functional, environmental, integration, and procurement criteria. The criteria were intended to identify sensors that were relevant to outdoor lighting applications and could be independently evaluated under the study conditions.

- **Intended application:** Sensors Candidate technologies and products identified through the literature and industry review were screened using functional, environmental, integration, and procurement criteria. The criteria were intended to identify sensors that were relevant to outdoor lighting applications and could be independently evaluated under the study conditions, including streetlighting, crosswalks, parking facilities, and pedestrian pathways.
- **Detection capability:** Sensors were selected where their intended detection function was relevant to moving pedestrians, bicycles, vehicles, or general human presence.
- **Environmental protection:** Sensors were expected to be suitable for outdoor exposure. IP65 and IK08 were preferred screening targets where applicable, but lower ratings were considered for products marketed or specified for outdoor use.
- **Procurement feasibility:** Sensors were evaluated based on cost, commercial availability, and procurement within the project timeline.
- **Data access:** Sensors had to provide a hardwired output interface or equivalent accessible signal output to support external data logging and validation.
- **Operational independence:** Sensors were preferred if they could operate in standalone mode, minimizing dependence on proprietary networks or complete lighting-control systems.

SELECTED SENSOR TECHNOLOGIES

A total of six commercial sensor units were selected to represent PIR, LiDAR, thermal-imaging, and hybrid PIR + microwave sensing. The products were selected from the candidates identified through the industry review using the criteria described above. The selected sensors and key manufacturer-reported specifications are summarized in Table 9.

Table 9. Selected technologies and manufacture-reported specifications.

Product	Technology	Typical Integration	Detection	FOV	Range	Mounting height	Cost	Intended applications/notes
Lumawise Circle	PIR	Into fixture	Cars, bicycles, pedestrians, wheelchairs	360° Down	Ø10m to Ø15m, circular (mounting height)	5m – 12m	\$90	fit into the Zhaga-D4i ecosystem
RAB	PIR	Wall/Pole	Cars, bicycles, pedestrians, wheelchairs	180° Out, 360° Down	18m x 18m	2m – 3m	\$140	Ideal for security application
Lumawise Rectangle	PIR	Into fixture	Cars, bicycles, pedestrians, wheelchairs	360° Down	15m x 5m	5m – 12m	\$90	fit into the Zhaga-D4i ecosystem
Optex REDSCAN RLS-2020S	LiDAR	Pole	Pedestrian	95° Forward	20 x 20 m	horizontal mode: $\geq$ 0.5 m	\$2000	Outdoor intrusion detection
TrafiOne (FLIR)	Thermal Imaging	Pole	Pedestrians, cyclists, motorcycles, cars	95° Forward	Pedestrian-bicycle: 0 - 12 m	3.5-6m	\$2000	Curbside and on-crossing pedestrian and bicycle presence detection.
Bosch OD850 TriTech	PIR + Microwave	Pole	Pedestrian	90° Forward	15 m×15 m		\$248	Ideal for security application

The selected sensors represented different optical, imaging, ranging, and hybrid sensing architectures. Detailed information on the working principle, physical and sensing architecture, manufacturer-defined coverage, key construction characteristics, and configuration of each selected sensor is provided in Appendix A.

Sensor Test Configurations and Mounting

The selected sensors differed in mounting geometry, detection pattern, processing, and output behavior; therefore, each was configured according to its operating architecture and the objectives of the experiment. The Bosch OD850 was tested in both PIR-only and PIR +

microwave AND configurations, resulting in seven analyzed sensor configurations (Figure 6. Diagram. Data correction example (left) and distance calculation (right). Analysis labels were assigned according to the primary sensing technology represented by each configuration. Because four PIR configurations were evaluated, these were designated PIR-1 through PIR-3, and two hybrid configurations: Hyb-OR and Hyb-AND, while the remaining configurations were designated LiDAR, and Thermal. In the Bosch OD850's AND mode, a detection output is generated only when both the PIR and microwave sensing channels simultaneously meet their detection criteria.

Table 10. Primary tested sensor configurations

Sensor configuration	Naming convention	Tested mounting	Detection configuration	Key tested settings
LUMAWISE Circle	PIR-1	6 and 12 m, downward facing	PIR, circular ground-coverage lens	Minimum 1-s output
LUMAWISE Rectangle	PIR-2	6 and 12 m, downward facing	PIR, corridor-focused lens	Minimum 1-s output
RAB	PIR-3	3 m, outward/downward facing	180° outward and 360° downward PIR coverage	Minimum 5-s output
Bosch Dual (PIR or microwave)	Hyb-OR	3 m, outward facing	PIR channel of Bosch OD850	Standard sensitivity; minimum 2-s output
Bosch Dual (PIR and microwave)	Hyb-AND	3 m, outward facing	PIR + microwave LTD	Standard PIR sensitivity; AND mode requiring both channels to qualify; minimum 2-s output
Optex REDSCAN RLS-2020S	LiDAR	1.2 m; horizontal-scan plane	20 × 20 m rectangular LiDAR detection area, 95° scan	Outdoor mode; medium sensitivity; 1-cm minimum target width; environmental-resistance processing; standard non-expansion area; approximately 2-s output
TrafiOne 195	Thermal	3 and 6 m; approximately 15° below horizontal	160 × 120 thermal image, 95° field of view	Standard and directional presence enabled; 90° directional-deviation setting; minimum delay and extend settings; thermal analytics only

Technology-based labels support comparison of the tested sensing approaches but do not imply that the performance of an individual product or configuration represents all sensors using that technology.

Orientation definition

The sensors under test were installed on the portable light pole and a sensor-specific reference direction was defined as the 0° orientation. The test grid (1m x 1m) and user trajectories remained fixed while the sensor was rotated counterclockwise in 45° increments (Figure 1). At 0° , the grid was located primarily within the left-hand sector of the sensor reference axis. At 45° , the user paths were positioned obliquely relative to the sensor axis. At 90° , the sensor axis was approximately aligned with the longitudinal direction of the grid, such that users traveled predominantly toward or away from the sensor. This approach changed the relationship between the fixed user paths and the sensor detection pattern without changing the physical test grid.



Figure 1. Plan-view definition of pole placement and sensor orientation relative to the fixed experimental grid.

Physical Mounting

For the forward-facing Bosch, TrafiOne, and Optex configurations, the vertical rotation axis was aligned with the lateral centerline of the sensor housing/detection aperture. For the RAB sensor, the center of the sensor head was aligned with the center of the downward-facing spherical lens to define the rotation axis. These references were maintained during rotation about a consistent spatial origin.

For the downward-facing LUMAWISE sensors, each unit was installed on a horizontal platform mount with annotated angular positions, and the center of the lens was aligned with the vertical axis of rotation. The Optex configuration used the standard 20×20 m, 95° horizontal detection area and was intentionally mounted at 1.2 m with its horizontal-scan plane approximately parallel to the ground to intersect pedestrians, bicyclists, and wheelchair users. The lowest available minimum target-width setting of 1 cm was selected to reduce the likelihood of missing narrow target features, particularly portions of the bicycle–rider profile intersecting the scan

plane. Outdoor mode, medium sensitivity, environmental-resistance processing, and the standard non-expansion detection area were used.

For TrafiOne, one large pedestrian-detection zone was configured to cover the visible portion of the experimental grid and was redrawn after each sensor-orientation change. Masking was applied where necessary. At both mounting heights, the sensor was aimed approximately 15° below horizontal. Standard and directional presence modes were enabled, the directional-deviation setting was 90°, and the delay and extend settings were minimized. Detection was based on thermal analytics.

INDEPENDENT VARIABLES

The study evaluated sensor configuration, road-user type, sensor orientation, and mounting height. Ambient and pavement-surface temperatures were recorded as environmental covariates. The factors and their levels are summarized in Table 11.

Table 11. Independent Variables

Factor	Class	Levels
Sensor Configuration	Between sensor	PIR, LiDAR, Thermal Imaging, Hybrid
Road-user type	Crossed factor	Pedestrian, Bicycle, Wheelchair, Vehicle.
Sensor orientation	Restricted crossed factor	0°, 45°, 90° common; additional 45° increments for omnidirectional sensors
Mounting height	Restricted by sensor	1.2, 3, 6, or 12 m depending on configuration

Road-User Type

Road-user type represented the primary users evaluated and included pedestrian, bicyclist, wheelchair user and vehicle. User speed was not independently manipulated or analyzed as an experimental factor. Movement speed varied naturally with road-user type and was therefore considered part of the tested road-user condition rather than a separate effect.

Sensor Orientation and Relative Motion

Sensor orientation varied relative to the fixed experimental grid to change both field-of-view alignment and user movement relative to the sensing pattern. The common orientations were 0°,

45°, and 90°. These orientations were selected to represent three distinct sensor-to-path geometries: predominantly transverse/lateral movement at 0°, oblique movement at 45°, and predominantly longitudinal or toward/away movement at 90°. Together, they provided a consistent basis for evaluating sensitivity to both user-motion geometry and sensing-footprint alignment across the different sensor architectures. Additional 45° increments through 315° were evaluated for the LUMAWISE configurations to characterize their broader coverage patterns. Users traversed each grid line in both directions. Toward-versus-away traversal direction was therefore part of the test protocol but was not modeled as a separate experimental factor. Changes with sensor orientation reflected how the fixed travel paths intersected the sensor field of view.

Mounting Height

Mounting height was included as a restricted experimental factor because the applicable heights differed among sensor configurations. Where feasible, sensors with a manufacturer-specified mounting-height range were evaluated at more than one height to examine the effect of installation height on detection performance. Sensors with a fixed or study-specific mounting configuration were evaluated at a single height. The tested heights for each configuration are provided in **Error! Reference source not found..**

Environmental Covariates

Ambient air temperature and pavement-surface temperature were recorded during testing and evaluated as observational covariates. Temperature was not experimentally controlled.

DEPENDENT VARIABLES

Three primary performance measures were evaluated: detection range, spatial coverage, and detection rate.

Detection Range

Detection range represented the minimum and maximum distances from the sensor at which detections were reliably supported under the tested conditions.

Coverage

Detection coverage described how the estimated minimum and maximum detection boundaries changed with sensor orientation and, where applicable, mounting height. These directional bounds were used to characterize the spatial distribution of detection around the sensor under the tested orientations.

Detection Rate

Detection rate was defined as the proportion of sampled target-present position records with an active sensor output within the sensor configuration's accepted practical range. It was therefore a position-based measure and did not represent the percentage of complete users or traversals successfully detected. Target-present positions beyond the accepted practical range were excluded from the detection-rate analysis.

EQUIPMENT AND TEST FACILITY

Portable Light Pole

The sensors under test were installed on the portable light pole using custom mounting platforms developed in-house to accommodate the different physical mounting requirements while providing a repeatable azimuth rotation reference. An aerial lift was used to install, align, and adjust the sensors in place. The GPS coordinates of the pole location were recorded to provide a fixed spatial reference for data analysis.

Experiment Site

The study was conducted on the paved test area at the VTTI building (**Error! Reference source not found.**). The site measured approximately 200 m in length and 12 m in width and included a single open entrance that was controlled using traffic-management devices during testing. A portion of the paved used for sensor testing was marked with a one-meter by one-meter grid. The grid provided a standardized spatial reference for defining movement paths, controlling test trajectories, and supporting later spatial analysis of sensor detection range and coverage.

Detection Data Logger

A custom-built detection data logger was used to record sensor output states with corresponding timestamps. The same data logging system was connected to each sensing configuration to maintain consistency across tests. A rotary switch allowed the research team to switch between sensors without rewiring the system. The data logger also included an LED status indicator for visual confirmation of sensor activation during testing and provided a protected AC-to-DC power supply for the sensors under test.

Data Acquisition Systems

Ground-truth position and timing data were recorded using dedicated data acquisition systems. Experimenters carried a Pedestrian Data Acquisition System (PedDAS) unit to record pedestrian, bicycle, wheelchair and vehicle movement trajectories across the marked grid. The PedDAS system provided position data with an approximate tolerance of 0.9 m (Figure 2).



Figure 2. Pedestrian Data Acquisition System (PedDAS)

Target Objects

The study used walking pedestrians, bicycle riders, wheelchair users, and motor vehicles as target objects. The selection and configuration of test objects were aligned as closely as feasible with ANSI C136.54 (Avotins et al., 2021), which specifies representative conditions for occupancy-detector testing, including human walking, human riding a bicycle, and motor vehicle targets, with reference to typical speeds, body or vehicle dimensions, thermal conditions, and clothing or configuration requirements. These reference conditions were used to guide the selection of test objects and test procedures.

Environmental Measurement

Ambient air temperature and pavement-surface temperature were recorded for each test condition so that detection performance could be evaluated in relation to environmental conditions. Pavement-surface temperature was measured using the handheld infrared temperature instrument while the corresponding ambient air temperature was obtained from the AccuWeather website.

DATA COLLECTION PROCEDURE

The data collection procedure was organized by sensor configuration, mounting height, user type, sensor orientation angle, and repetition number. Before each test condition, the research team verified that the correct sensor configuration was installed, the mounting height matched the test matrix, the sensor was oriented to the prescribed angle, the grid was properly established, and the data logger and ground-truth tracking systems were functioning.

Detection Range and Coverage Procedure

Detection range and coverage testing was conducted to characterize the spatial extent of each sensor's detection area. The grid and user movement paths remained fixed while the sensor was rotated to the prescribed orientations. Directional sensors were evaluated over the relevant orientation range, while sensors with broader or omnidirectional coverage were evaluated over a larger angular range where applicable.

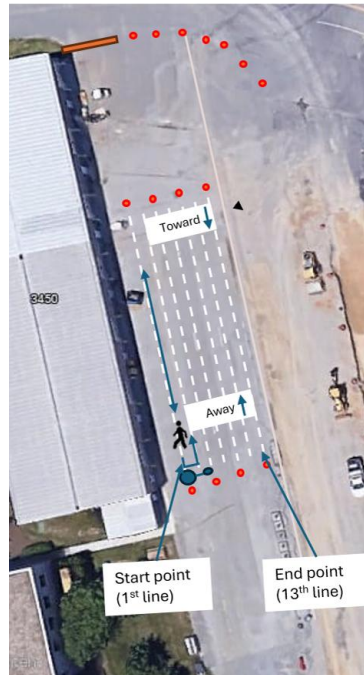


Figure 3. Experimental grid for pedestrian, bicycle and wheelchair trials.

Pedestrian, bicycle, and wheelchair users traversed the grid along predefined lines and directions while carrying a PedDAS unit (Figure 3). The PedDAS recorded the user's position and timestamp throughout each traversal. Sensor activation data were recorded separately by the detection data logger.

Each repetition consisted of sequentially traversing all grid lines. At the beginning of a repetition, a double button press marked the event start. The user then traveled away from the pole along the first grid line and returned along the same line. Single button presses marked the end of the outbound traversal, the end of the return traversal, and the transition to the next gridline. This sequence was repeated across the grid, and a double press after completion of the final line marked the end of the repetition. These event and subevent markers provided reference points for aligning the user-position data with the recorded sensor output during post-processing.

For each sensor orientation and user condition, the full grid traversal was completed according to the prescribed number of repetitions. Repeated trials were included at selected angles and

conditions to assess detection consistency. Ambient air and pavement-surface temperature were documented for test conditions, together with the corresponding test times.

The complete detection range and coverage test matrix, including sensor type, user type, orientation angle, repetition count, and mounting height, is provided in Appendix A.

Mounting-Height Assessment

A mounting-height assessment was conducted for Lumawise (PIR-1 and PIR-2) and TrafiOne (thermal) at selected mounting heights within manufacturer-specified ranges. The purpose of this assessment was to determine how installation height affected detection range, coverage, and detection rate.

The mounting-height assessment did not repeat the full angular matrix used in the range and coverage assessment. Instead, selected orientation angles were tested to provide targeted comparisons across mounting heights. The specific combinations varied by sensor and are provided in Appendix B; therefore, mounting height and orientation were not fully crossed for every configuration. The same grid traversal, sensor-output logging, ground-truth trajectory recording, and field documentation methods used in the detection range and coverage assessment were used for the mounting-height assessment.

Vehicle Detection and Speed Procedure

Vehicle testing was conducted to evaluate sensor response to motor vehicle movement, lane position, and travel direction. A VTTI test vehicle was driven through the test grid along prescribed lane paths (Figure 4) at an approximate speed of 20–25 mph, consistent with the final data collection protocol.



Figure 4. Vehicle detection grid layout.

Field Notes and Data Handling

During testing, field notes were recorded for conditions that could affect interpretation of the data, including unexpected detections, accidental movement during gaps between trials, unusual environmental conditions, equipment issues, or deviations from the planned procedure. Following each test session, sensor-output files, ground-truth trajectory files, data collection sheets, and field notes were transferred to the project data storage location for post-processing and quality control.

Data Processing and Performance Metrics

After data collection, sensor detection timestamps were matched with the corresponding PedDAS timestamps. This synchronization allowed each sensor output state to be associated with the target user's position and movement condition at the corresponding time.

For detection range and coverage analysis, matched position and detection data were used to identify the spatial distribution of detected positions by sensor orientation and mounting condition. Quantile regression was then used to estimate the minimum and maximum practical detection boundaries, as described in Data Analysis Section.

After the practical detection range for each sensor configuration was established, target-present records outside those bounds were excluded from the detection-rate analysis. Detection rate was then calculated as the proportion of detected records among the remaining within-range position records.

DATA ANALYSIS METHOD

After data matching was performed the data was checked for reliability of GPS position. The GPS accuracy of each data point was vital to the analysis as the detection distance required accurate location of the object. The vehicle-position data did not meet the spatial-quality requirements needed to reliably associate sensor output with vehicle location. Vehicle trials were therefore excluded from the detection-range, coverage, and detection-rate analyses. The remaining analyses included pedestrian, bicycle, and wheelchair trials.

An example movement profile is shown in Figure 5 where the pedestrian experimenter travelled up and down each of the 13 red grid lines. These points represent the full path and contain detections alongside non-detections. The pre-experiment expectation was that each GPS path would overlap the appropriate gridline and that each path would turn around when it reached the pole location. Experimental protocol dictated strict pathing along the red grid lines and video reduction validated the pedestrian pathing; however, the resulting GPS locations showed trial-specific spatial offsets.



Figure 5. Diagram. Geospatial offset example.

The video reduction tagged each data point with the grid line the experimenter travelled along. The known grid paths and turnaround points were validated through video reduction; therefore the research team performed a data correction to align the pathing longitudinally along the grid. The corrected pathing was then snapped to the gridline to eliminate small lateral variation in position. The left panel of Figure 6 shows this correction for a pedestrian path travelling along gridline 1. The raw data produced green path A, which was significantly offset from gridline 1.

The research team re-aligned path A to path B so that the turnaround point was at the end of the grid. Path B was then snapped to gridline 1 as the research team was confident that the experimenter carefully travelled along the gridline. This process resulted in a clean dataset that was corrected for the lateral and longitudinal offset present for each path. Distance to the pole location (bottom left of the grid) was then calculated for each point, as shown in the right panel of Figure 6. Subsequent statistical analyses modeled the distance of successful detections and the detection rate.

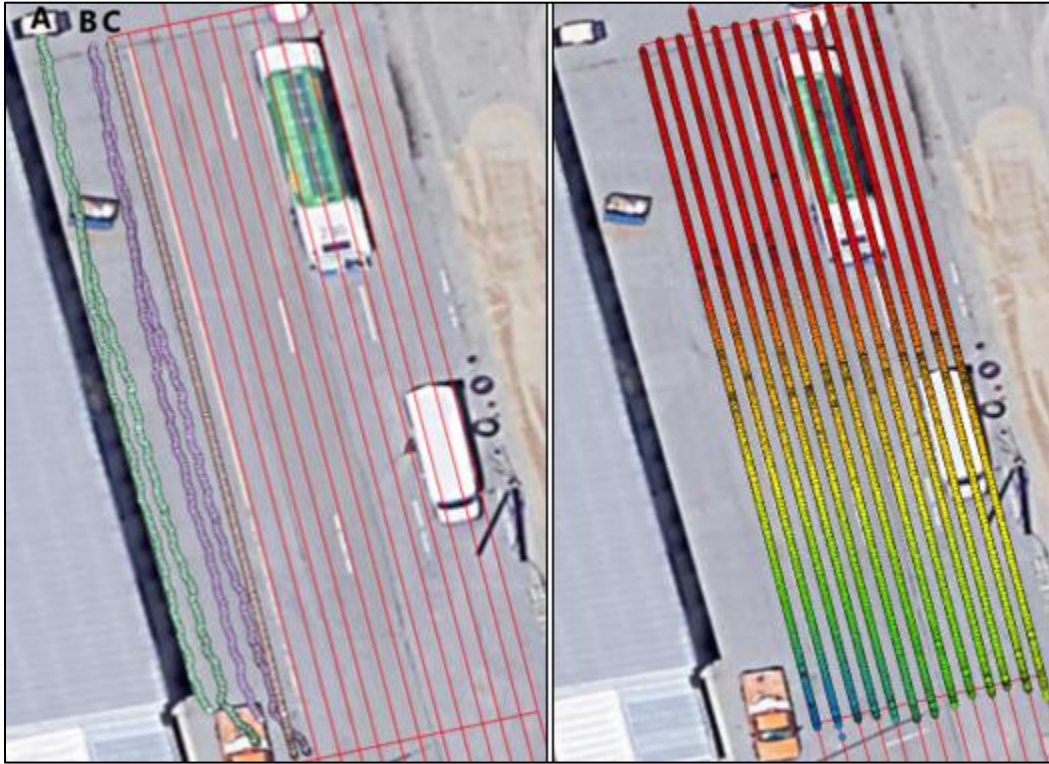


Figure 6. Diagram. Data correction example (left) and distance calculation (right).

Detection rate was evaluated using linear mixed modeling (LMM). LMMs take the traditional form shown in Figure 7 by fitting a model with a linear combination of random and fixed effects. Each detection rate model included experimenter-to-experimenter variation as a random effect alongside a combination of the following fixed effects: sensor configuration, user type, motion angle, mounting height, ambient temperature, and surface temperature. Models also specified that repeated measures were taken for some trials (outlined in Appendix B).

$$y = X\beta + Z\mu + \varepsilon$$

Figure 7. Equation. Linear mixed model regression equation.

Main effects and lower order interactions were kept in the models to preserve hierarchy regardless of their significance. Post hoc analyses were conducted using a differences of least-

squares means procedure to evaluate pairwise comparisons. Within family comparisons requiring multiple post hoc tests were corrected using Tukey's honest significant difference methodology to keep the familywise error rate at the study's significance level of 0.05 (Abdi & Williams, 2010). The detection rate visualizations contain error bars which represent the 95% confidence interval and significant difference via letters above the model estimate bars, using a technique called compact letter display (Piepho, 2018).

Detection range and coverage were evaluated using a quantile regression procedure. Quantile regression was chosen for its ability to estimate conditional quantiles at any specified point within the dataset, as opposed to standard measures of centrality. Extreme quantiles of 0.001 and 0.999 were initially used as estimate of the minimum and maximum detection range. Models were fit to estimate each desired quantile and contained a combination of the following fixed effects: sensor configuration, motion angle, and mounting height.

The estimated quantile curves were then reviewed for sparse detections at the extreme tails. When an extreme boundary was supported by few detections and nearby observations were predominantly non-detections, adjacent quantiles were reviewed to establish a reliable range. The resulting minimum and maximum bounds were defined as the accepted practical detection range: the range supported by a consistent pattern of detections rather than isolated detections at the distribution tails. These accepted bounds were used as the practical detection ranges reported in the Results and to define the records retained for detection-rate analysis.

RESULTS

Results are presented for three dependent measures: detection range, detection coverage, and detection rate. Detection range represents the overall practical bounds estimated after pooling observations across tested conditions, whereas detection coverage describes how those bounds varied by sensor orientation and mounting height. Detection rate represents the proportion of target-present position records with an active sensor output within the accepted practical detection range.

DETECTION RANGE

Quantile regression was used to estimate minimum and maximum detection distances for each sensor configuration. Extreme quantile estimates were reviewed for sparse detections at the distribution tails, and adjacent quantiles were selected when they provided a more reliably supported practical boundary.

The configuration-specific quantile estimates, tail evaluations, and detection-distance distributions are provided in Appendix C. The accepted practical ranges are compared across sensor configurations below.

Figure 8 compares the accepted practical detection ranges across the seven sensor configurations. Practical minimum detection distances were relatively similar across configurations, ranging

from approximately 3.4 ft for PIR-2 to 6.7 ft for Hyb-OR. Greater differences were observed in the maximum detection distances. Thermal provided the farthest practical maximum detection distance at 116.5 ft, followed by Hyb-OR (97.4 ft), LiDAR (82.0 ft), PIR-3 (74.2 ft), Hyb-AND (64.9 ft), PIR-1 (63.3 ft), and PIR-2 (58.7 ft) sensors. The Thermal configuration therefore extended approximately 19.6% farther than the Hyb-OR sensor, which had the second-farthest maximum detection distance.

The four PIR configurations produced notably different practical maximum distances, ranging from 58.7 ft for PIR-2 to 97.4 ft for Hyb-OR. Thus, substantial variation was observed not only among sensing technologies but also among configurations using the same underlying sensing technology. The Hyb-AND configuration provided a shorter practical maximum distance than the Hyb-OR configuration of the same Bosch OD850 unit (64.9 versus 97.4 ft).

These ranges represent the overall practical detection bounds after pooling observations across the tested orientations, mounting height and road-user conditions. Variation in detection extent across sensor orientation and mounting height is examined in the Detection Coverage section.

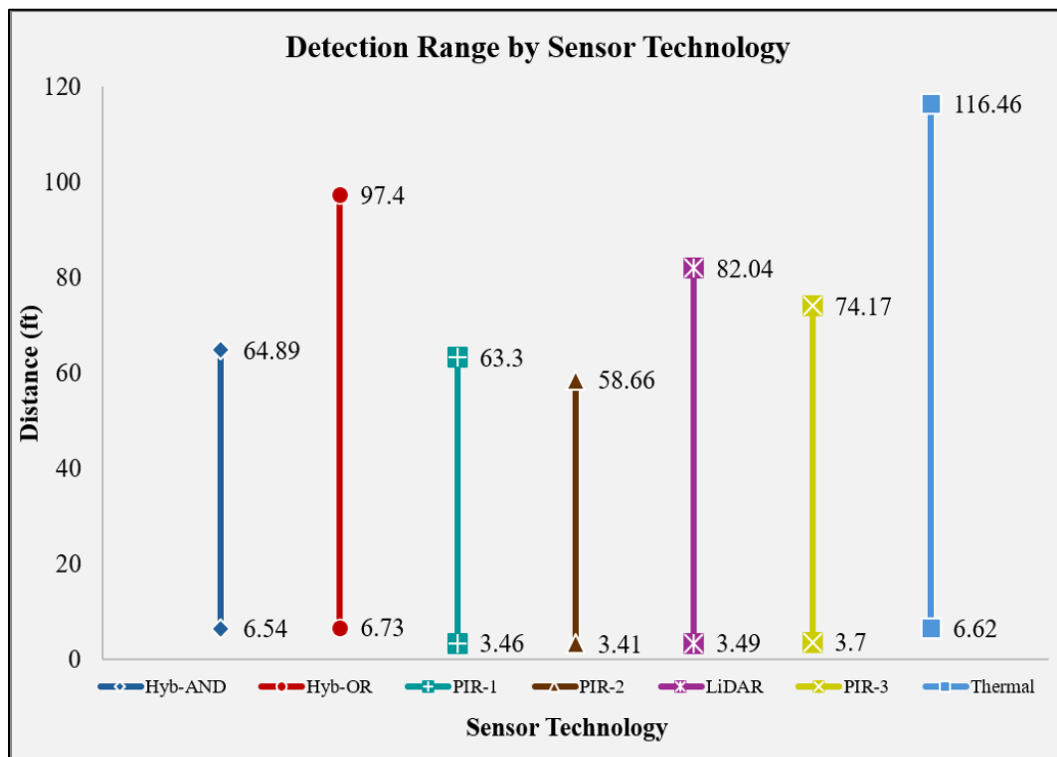


Figure 8. Graph. Detection range by Sensor Technology.

DETECTION COVERAGE

Detection coverage was assessed for each sensor configuration using a quantile regression procedure. The regression fit models with sensor technology, mounting height, and motion approach angle as the main effects. The models estimated the minimum (0.01st quantile) and maximum (99.9th quantile) detection distances for each factor combination tested in this

research. Modeling utilized detections from all user types to establish a detection range for each sensor technology as it varied by mounting height and approach angle. Configuration-specific estimates, tables, and coverage plots are provided in Appendix D; comparisons across sensor configurations are summarized below.

Figure 9 compares maximum detection distance across the tested sensor configurations and orientations. Substantial differences were observed in both the extent and orientation dependence of detection coverage. The Hyb-OR maintained relatively consistent maximum distances of approximately 93–99 ft across the three common orientations (0° , 45° , and 90°). LiDAR and PIR-3 also showed relatively little variation across these orientations, with maximum distances of 80.6 to 84.8 ft, and 69.6 to 75.2 ft, respectively. Thermal showed substantially greater variation at 3m, increasing from 61.4 ft at 0° to 113.0 ft at 45° , and 105.9 at 90° . Thermal was additionally evaluated at 6 m only at the 90° orientation, where the maximum detection distance reached 116.5.

Differences were also evident among the PIR configurations. At 6 m, PIR-1 produced maximum distances of 55.7–67.5 ft across the eight tested orientations and exceeded PIR-2 at every corresponding orientation. PIR-2 varied more substantially, from 30.4 to 62.3 ft. Hyb-OR provided the greatest maximum coverage among the PIR configurations, whereas PIR-1 provided the most uniform coverage across the eight-orientation evaluation.

The Hyb-AND configuration produced maximum distances of 71.5 and 64.7 ft at 0° and 45° , respectively. A reliable estimate was not available at 90° , so its orientation coverage could not be compared across all three common orientations.

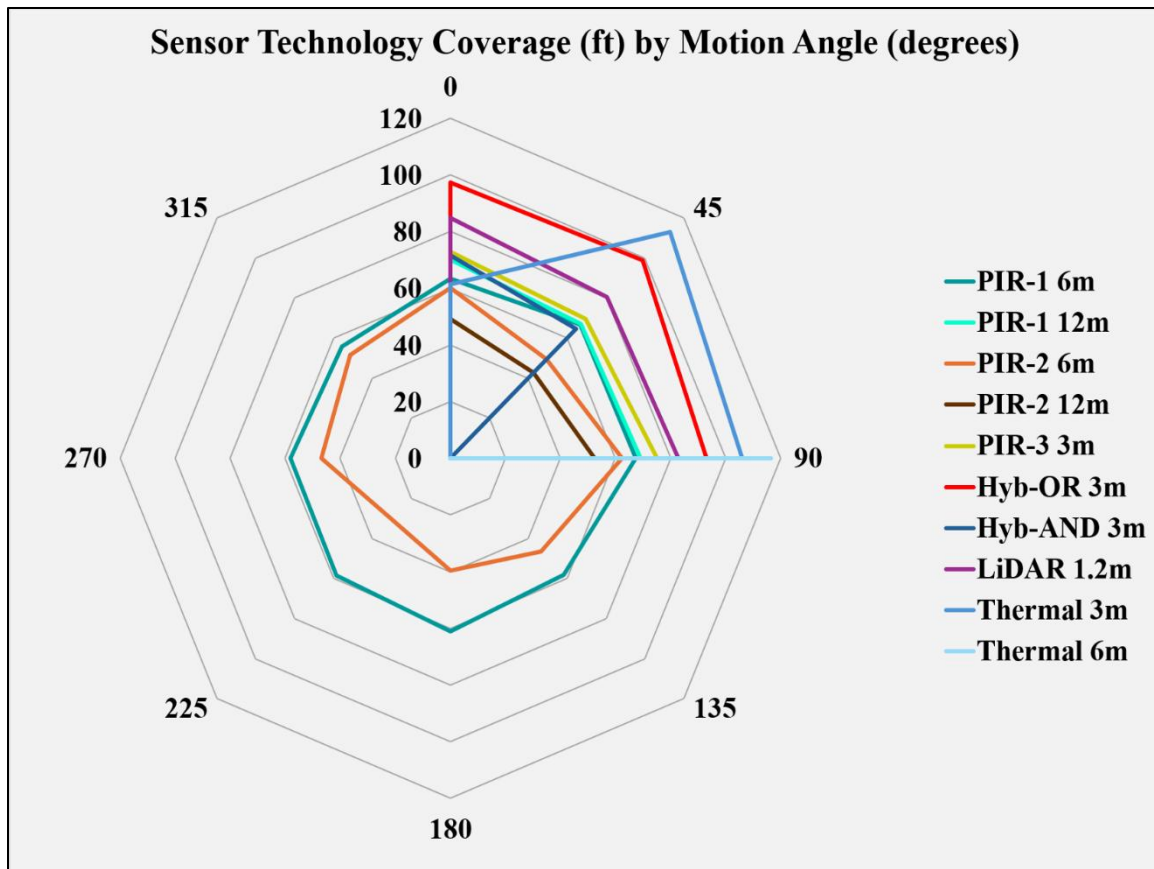


Figure 9. Graph. Maximum detection distance by sensor configuration and orientation.

DETECTION RATE

Detection-rate analyses included target-present position records within each sensor configuration's accepted practical range. Records beyond these bounds were excluded.

Sensor Configuration

The effect of sensor configuration type was statistically significant, as shown in Table 12, indicating that the detection rate for at least two of the sensors were significantly different. Post-hoc comparisons between sensor technologies were performed to determine where the significant difference was present.

Table 12. Type 3 test of fixed effects for sensor technology.

Effect	Num DF	Den DF	F Value	Pr > F
Sensor	6	380000	6483.40	<.0001

The mean detection rate estimates and pairwise comparison results are shown in Figure 10. Due to the large sample size, all sensor configuration comparisons were statistically significant. The LiDAR sensor (71%), which used LiDAR, detected the highest proportion of road users while

the Hyb-AND (13%) had the lowest. Amongst the sensors using only PIR configurations, Hyb-OR (56%), PIR-1 (55%), and Thermal (55%) were similar in magnitude, while the PIR-3 (42%) and PIR-2 (27%) had much lower detection rates.

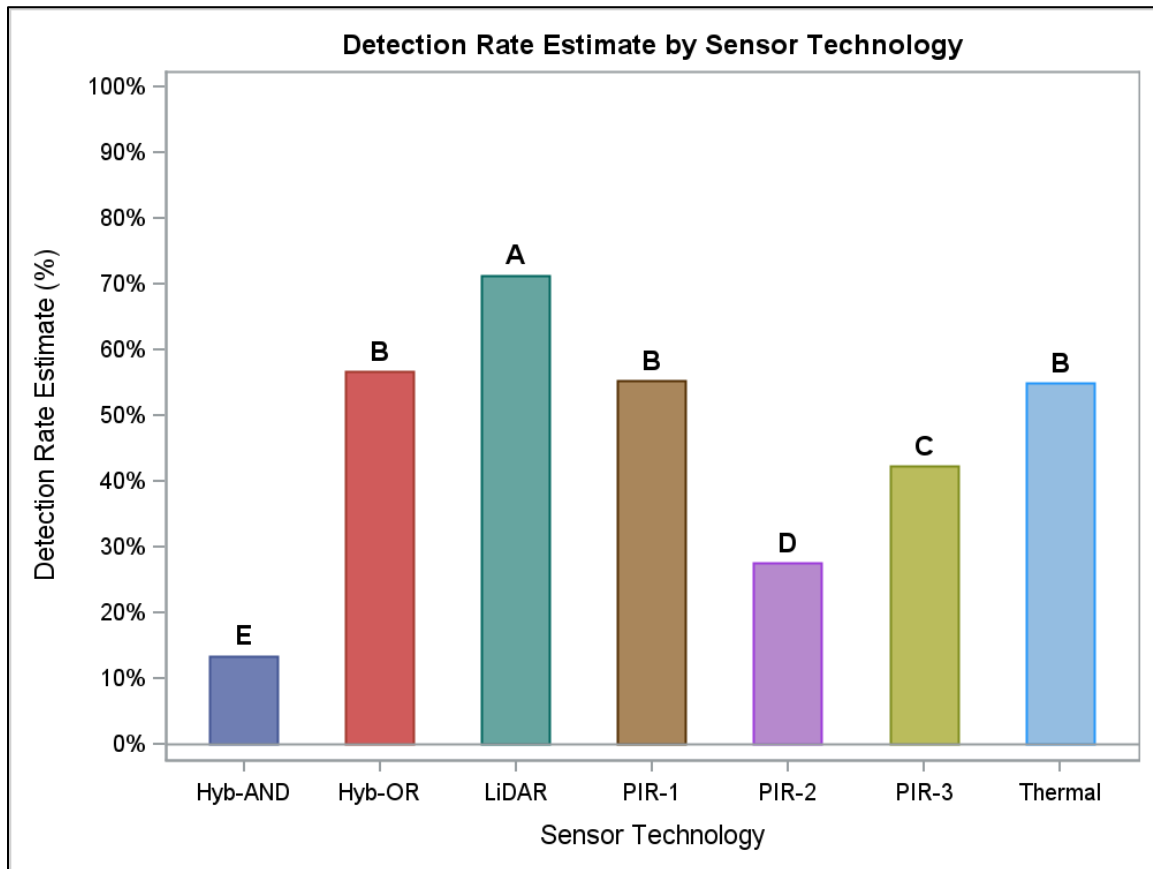


Figure 10. Graph. Detection rate estimates by sensor technology. Error bars represent 95% confidence interval.

Road-User Type

Road-user type, sensor configuration, and their interaction significantly affected detection rate (Table 13). Post-hoc testing was therefore focused on the interaction between sensor technology and user type to determine where the significant difference was present.

Table 13. Type 3 test of fixed effects for user type and sensor technology.

Effect	Num DF	Den DF	F Value	Pr > F
User Type	2	380000	392.16	<.0001
Sensor	6	380000	4618.78	<.0001
Sensor*User Type	12	380000	370.51	<.0001

As shown in Figure 11, the pattern of road-user effects varied by sensor configuration. LiDAR had detection rates of 72% for pedestrians and 76% for wheelchair users, both significantly higher than the 62% bicycle rate. A similar pattern was observed for the Hyb-OR; however, the detection rate was lower for all user types. PIR-3 and both PIR-1 and PIR-2, produced their

highest rates for bicycle users, while PIR-1 had higher rates than PIR-2 for each road-user type. Hyb-AND produced low rates overall, including very limited wheelchair detection. Significant road-user differences were present within each sensor configuration.

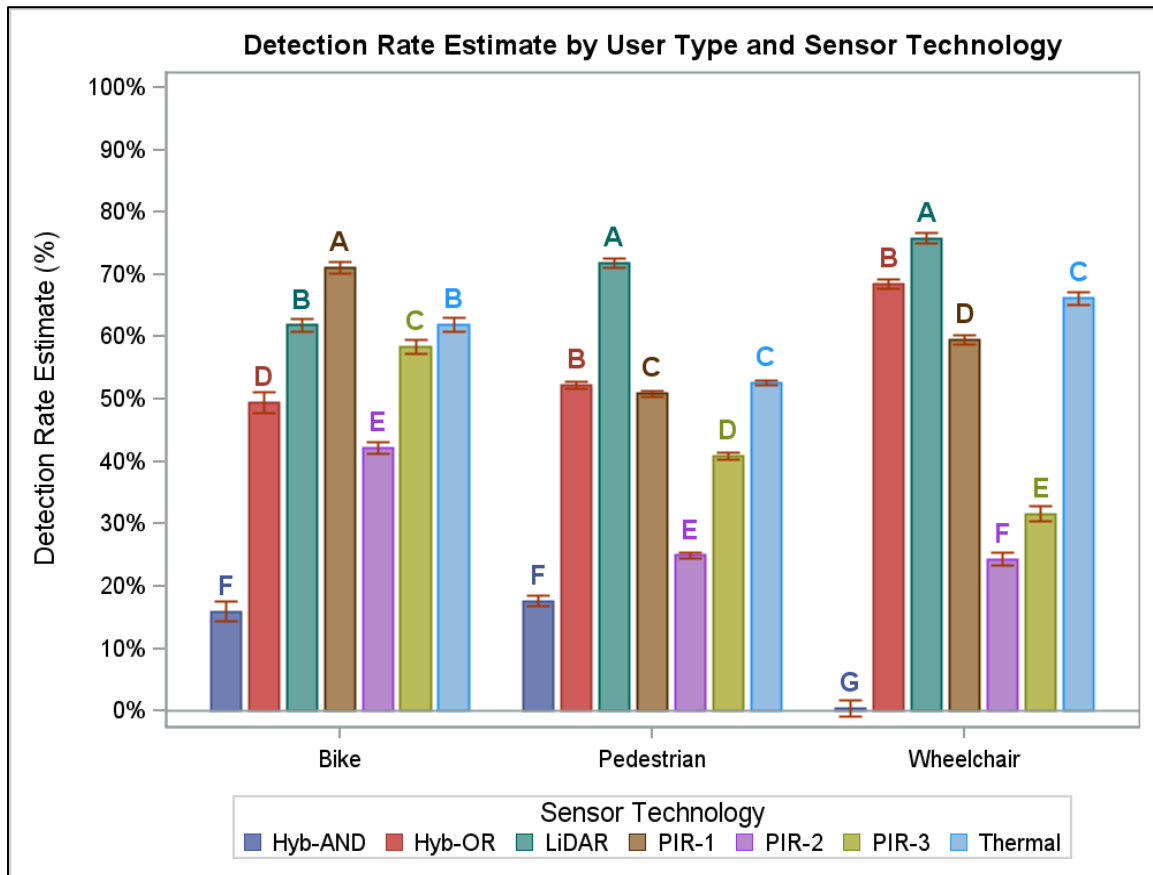


Figure 11. Graph. Detection rate estimates by user type and sensor technology. Error bars represent 95% confidence interval. Post-hoc comparisons within user type.

Sensor Orientation

Sensor orientation, sensor configuration, and their interaction significantly affected detection rate (Table 14). Post-hoc testing was therefore focused on the interaction between sensor technology and angle to determine where the significant difference was present.

Table 14. Type 3 test of fixed effects for motion angle and sensor technology.

Effect	Num DF	Den DF	F Value	Pr > F
Angle (°)	7	380000	642.79	<.0001
Sensor	6	380000	3952.66	<.0001
Sensor*Angle (°)	16	380000	477.11	<.0001

Figure 12 compares the commonly tested orientations of 0°, 45°, and 90°, where estimates were available. The LiDAR sensor demonstrated nearly twice the detection rate at 45° (95%) compared with 0° (48%) and 90° (52%). The Hyb-OR (72%) and Thermal (64%) also produced their highest detection rates at 45°, compared to 0° and 90°. The PIR-1 (55% to 59%) and PIR-3

(40% to 48%) sensors had consistent performance across angles, while the PIR-2 (14% to 36%) and Hyb-AND (11% to 21%) sensors had low detection rate from all three angles.

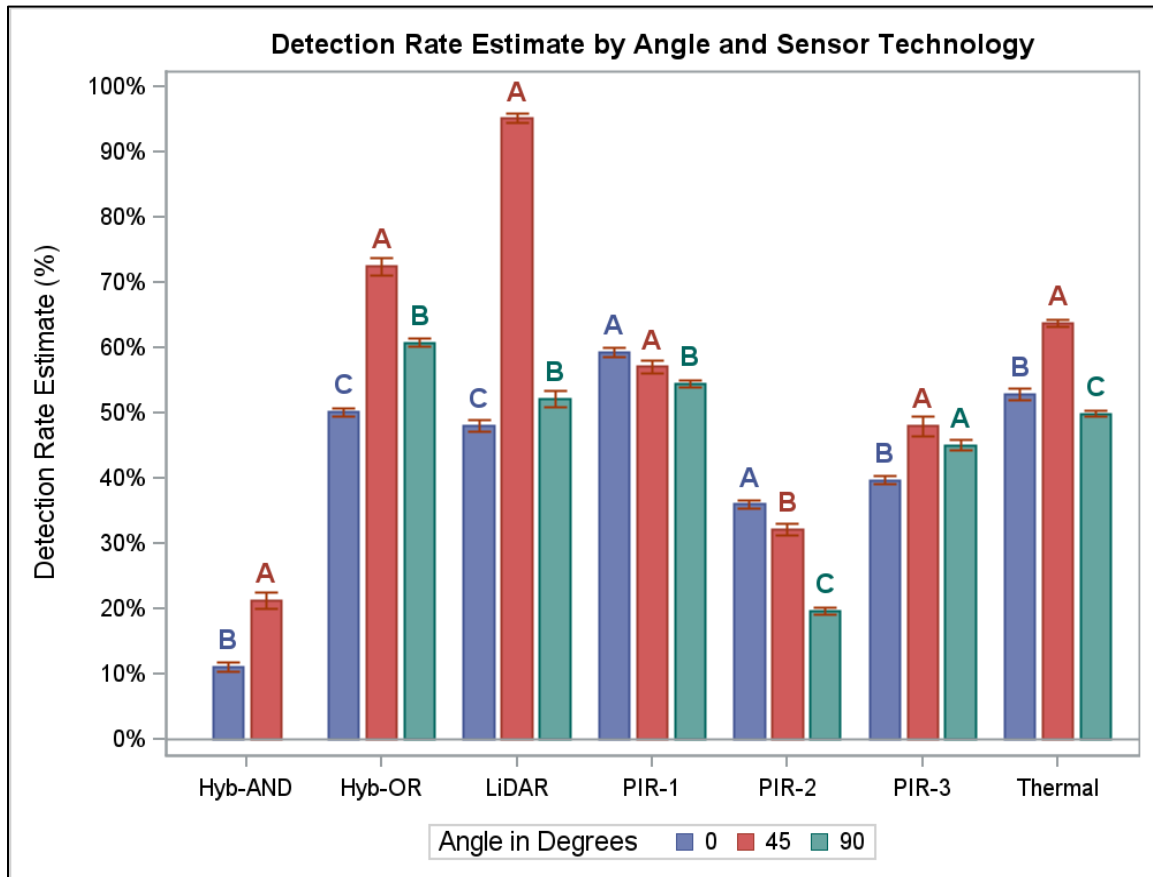


Figure 12. Graph. Detection rate estimates by motion angle and sensor technology. Error bars represent 95% confidence interval. Post-hoc comparisons within sensor technology.

Two sensors, PIR-1 and PIR-2, were tested across eight orientations to evaluate 360° coverage. Pairwise comparisons showed that orientation significantly affected detection rate for both sensors, as shown in Figure 13. Although rates differed among orientations, the PIR-1 sensor demonstrated similar detection rates for all approach angles except for 315° (68%), which was significantly higher. The PIR-2 sensor showed two general groupings of detection rates. The 0°, 45°, 135°, and 315° approach angles had similar detection rates while the 90°, 180°, 225°, and 270° approach angles had similar but significantly lower detection rates. Overall, the PIR-1 sensor had significantly higher detection rates at all approach angles than PIR-2.

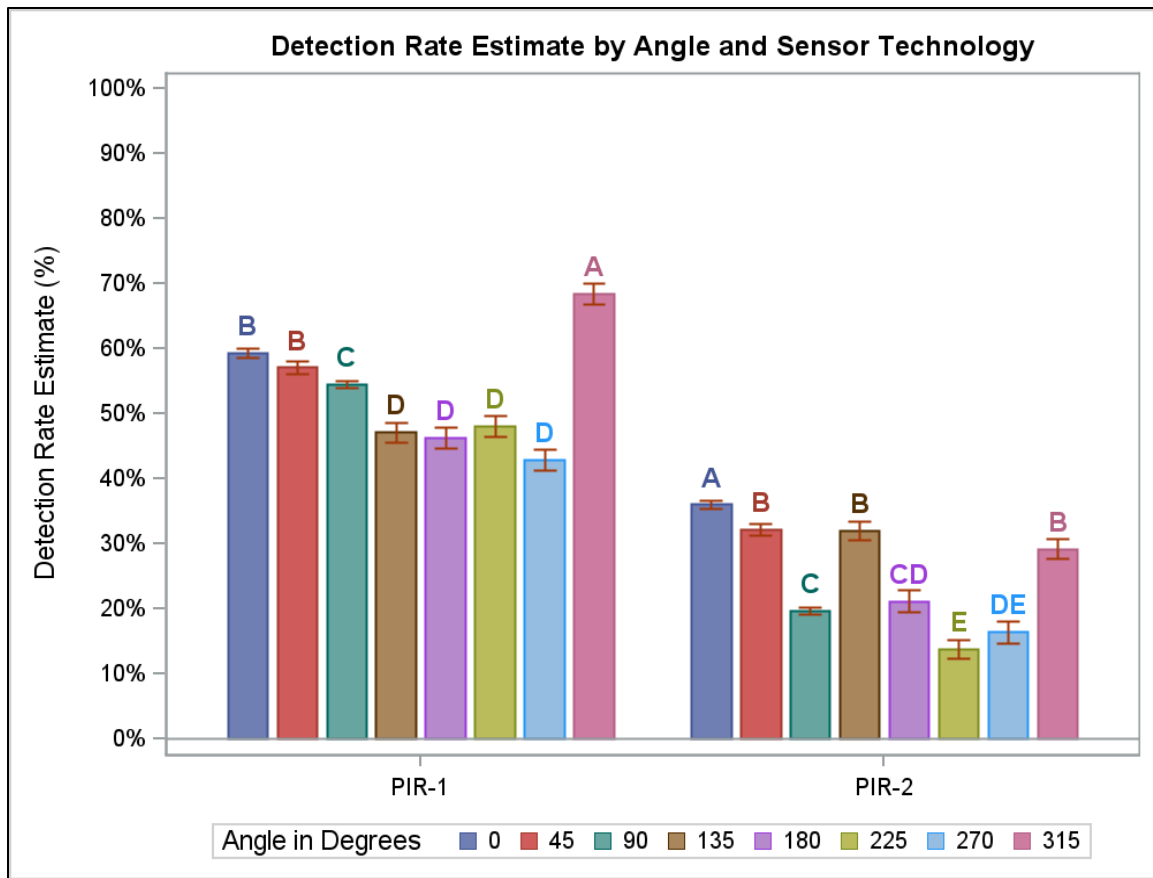


Figure 13. Graph. Detection rate estimates by motion angle for PIR-1 and PIR-2 sensors. Error bars represent 95% confidence interval. Post-hoc comparisons within sensor technology.

Mounting Height

Mounting height, sensor configuration, and their interaction significantly affected detection rate for the configurations included in the height analysis (Table 15). Post-hoc testing focused on the interaction between sensor technology and angle to determine how varying the mounting height influenced detection rate.

Table 15. Type 3 test of fixed effects for mounting height and sensor technology.

Effect	Num DF	Den DF	F Value	Pr > F
Mounting Height (m)	2	200000	1626.50	<.0001
Sensor	2	200000	4327.01	<.0001
Sensor*Mounting Height (m)	1	200000	459.15	<.0001

Mounting height was found to have a significant influence on the detection rate of the PIR-1, PIR-2, and Thermal sensor technologies. Overall, mounting height had a positive influence on detection rate for the PIR-1 and PIR-2 sensors, as shown in Figure 14. The detection rate for the PIR-1 sensor increased from 53% at 6 meters to 62% at 12 meters. Similarly, the detection rate for the PIR-2 increased, but doubled from 21% at 6 meters to 42% at 12 meters. Mounting height

had a negative influence on the Thermal sensor where the detection rate decreased from 57% at 3 meters to 48% at 6 meters.

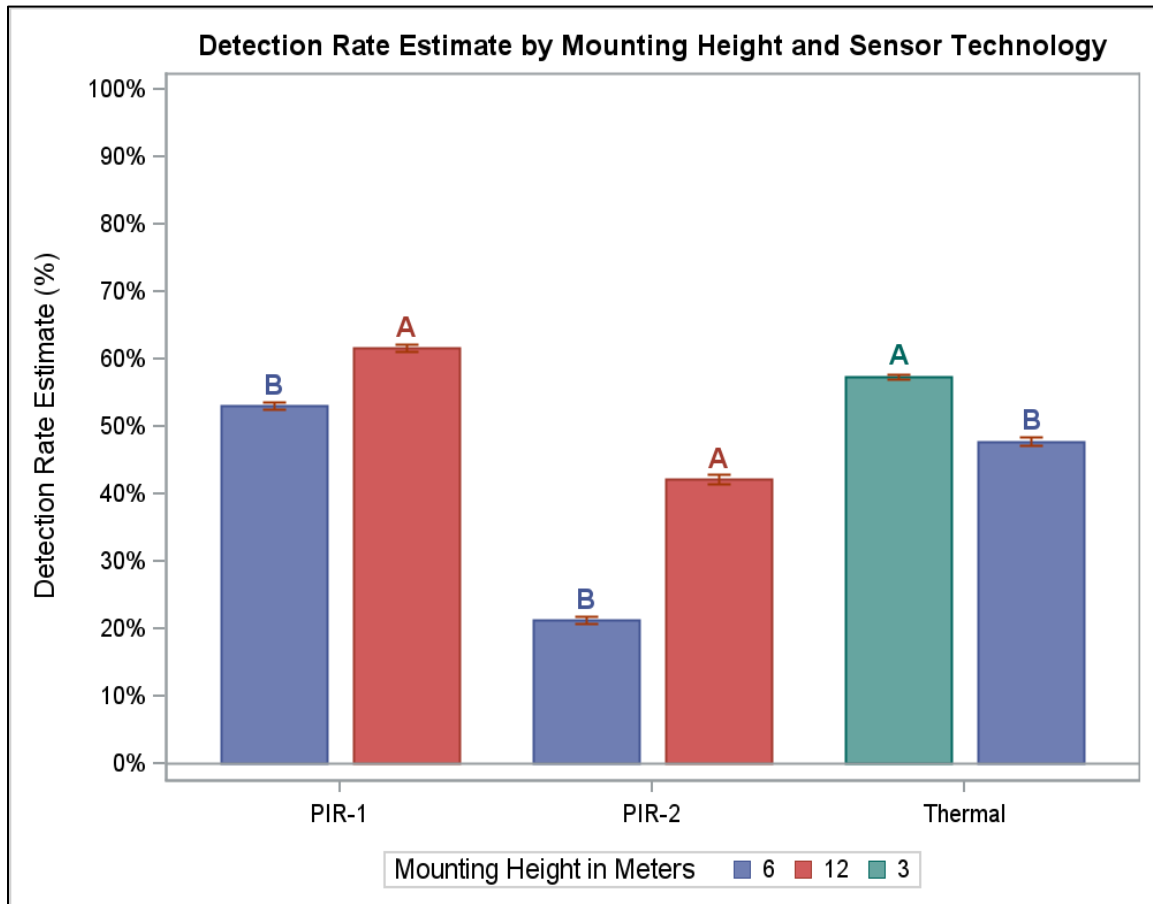


Figure 14. Graph. Detection rate estimates by mounting height and sensor. Error bars represent 95% confidence interval. Post-hoc comparisons within sensor technology.

Ambient Temperature

Ambient temperature and its interaction with sensor configuration were statistically significant (Table 16), but pairwise comparisons did not indicate a consistent pattern. Local regression curves were therefore used to summarize descriptive trends across the observed temperatures.

Table 16. Type 3 test of fixed effects for ambient temperature and sensor technology.

Effect	Num DF	Den DF	F Value	Pr > F
Ambient Temperature (°C)	30	380000	380.25	<.0001
Sensor	6	380000	2434.20	<.0001
Sensor*Ambient Temperature (°C)	10	380000	317.63	<.0001

The PIR-1, LiDAR, and Dual sensors demonstrated positive descriptive trends between detection rate and ambient temperature, as shown in Figure 15. PIR-2 and Hyb-OR demonstrated a negative trends, while the PIR-3 and Thermal sensors were generally neutral.

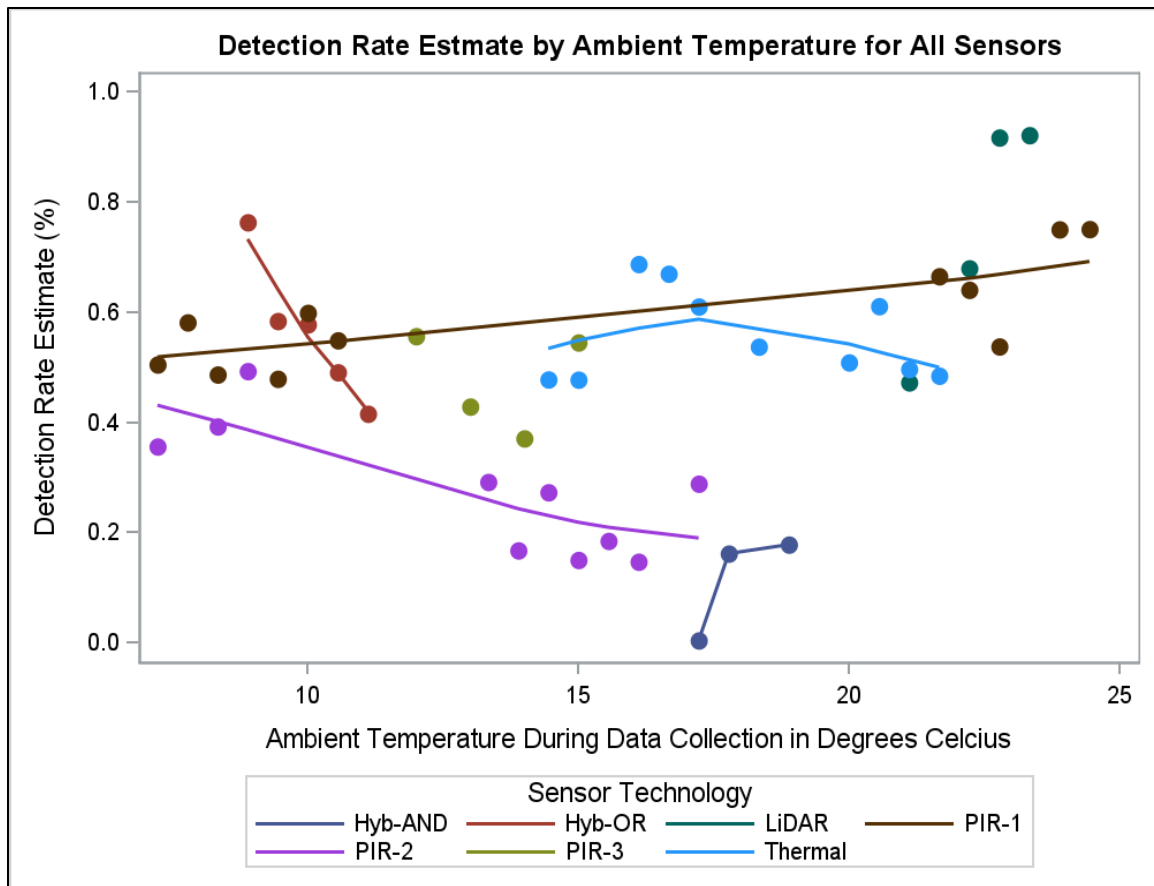


Figure 15. Graph. Detection rate estimates by ambient temperature and sensor configuration. Trendline represents a local regression fit.

Surface Temperature

Surface temperature and its interaction with sensor configuration were statistically significant (Table 17) but pairwise comparisons did not indicate a consistent pattern. Local regression curves were used to summarize descriptive trends across the observed surface temperatures.

Table 17. Type 3 test of fixed effects for surface temperature and sensor technology.

Effect	Num DF	Den DF	F Value	Pr > F
Surface Temperature (°C)	19	380000	398.91	<.0001
Sensor	6	380000	1333.43	<.0001
Sensor*Surface Temperature (°C)	9	380000	563.70	<.0001

The influence of surface temperature was evaluated using a local regression curve to estimate the overall direction of the relationship between sensor technology and surface temperature.

Detection rate was found to have a positive descriptive trends with surface temperature for PIR-1, LiDAR, Hyb-AND, and Thermal sensors, while PIR-2, PIR-3, and Hyb-OR showed negative or generally neutral trends as shown in Figure 16.

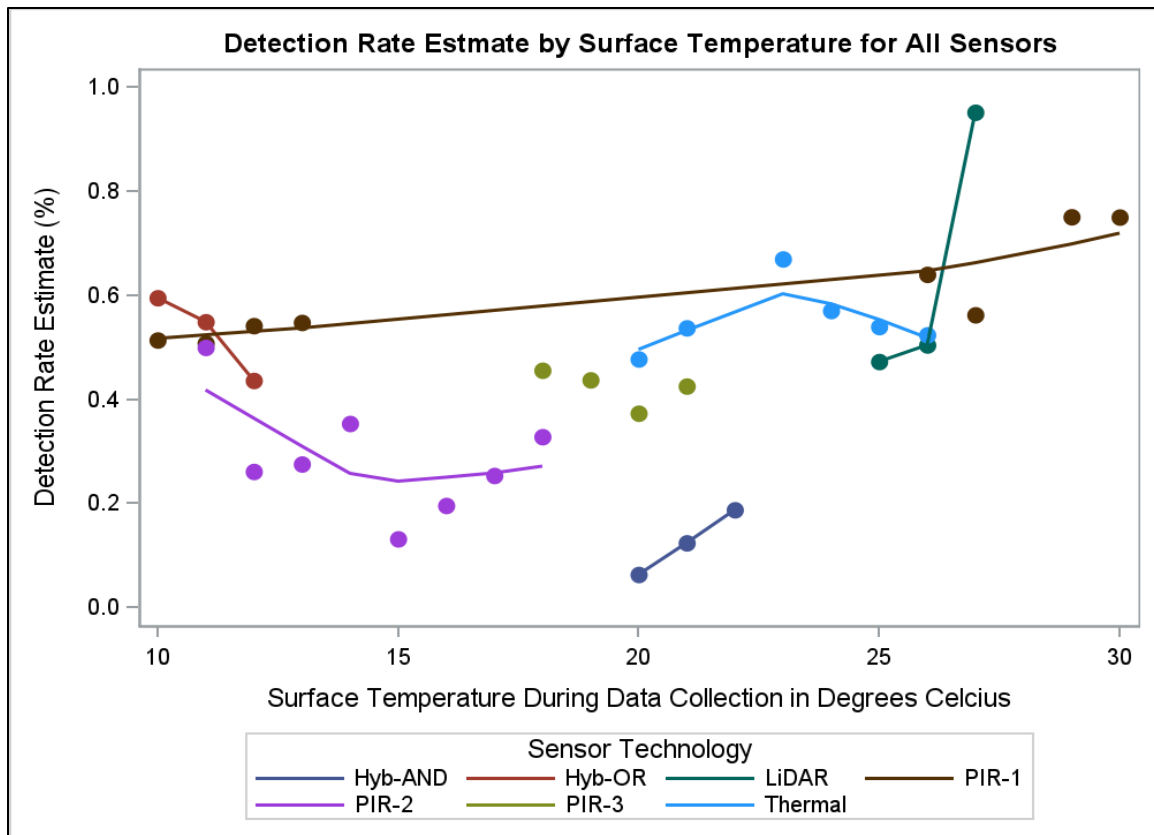


Figure 16. Graph. Detection rate estimates by surface temperature and sensor. Trendline represents a local regression fit.

Overall, the detection rate analysis showed that the LiDAR sensor had the highest detection rate across all variables considered while the Hyb-AND sensor had the lowest. User type, motion angle, and mounting height all significantly influenced the detection rate with the effect size and direction of the relationship varying by sensor technology. Temperature results were less conclusive where weak positive and negative relationships were found between temperature and sensor technology. Further testing would be needed to establish the relationship between ambient or surface temperature and the detection rate of the sensor technologies considered during this research.

DISCUSSION

The findings show that outdoor occupancy-sensor performance depends on both the sensing principle and how that principle is implemented. Thermal imaging, LiDAR, PIR, and hybrid PIR-microwave sensing differed in practical range, spatial coverage, within-range detection consistency, sensitivity to orientation, and response across road-user types. At the same time, substantial differences were observed within technology: PIR coverage changed with lens geometry and mounting, and the same hybrid hardware behaved very differently under OR and AND fusion logic. For practice, the technology category therefore defines the general detection

mechanism, while optics, field of view, mounting geometry, processing, and output logic determine whether that mechanism is appropriate for a particular lighting application.

For outdoor lighting control, sensor performance should be judged against the required lighting response rather than maximum detection distance alone. A useful sensing system must detect the intended users early enough and across enough of the approach area for the required luminaires to reach the intended light level, while avoiding unnecessary activation outside the area of interest. The discussion therefore compares the technologies in terms of detection range and coverage, consistency within that coverage, orientation and movement, road-user profile, installation/configuration, environmental considerations, and implications for integrating sensing with outdoor lighting.

DETECTION RANGE AND COVERAGE CHARACTERISTICS

The technologies provided different combinations of advance reach and spatial coverage. Thermal imaging produced the greatest potential reach, Hybrid-OR (logic: PIR or microwave) also provided long and comparatively stable outer coverage, LiDAR provided an intermediate but stable outer boundary, and PIR ranged from localized broad coverage to directional corridor or forward coverage depending on the optics. Hybrid-AND (logic: PIR and microwave) produced the most restrictive footprint. These differences are consistent with the different ways the technologies define occupancy: thermal imaging and LiDAR form spatial representations of the monitored area, PIR relies on target movement through optical zones, and hybrid sensing expands or restricts the usable footprint depending on how its sensing inputs are fused.

Thermal imaging demonstrated the strongest long-range potential, but the reach was not uniform across the monitored area. At the common 3-m mounting height, maximum distance was approximately 61 ft at 0 degrees, 113 ft at 45 degrees, and 106 ft at 90 degrees. The tested thermal system used a 95-degree two-dimensional LWIR field of view with software-defined detection zones. In the 0-degree condition, only a limited portion of the elongated grid was visible, effectively capping the measurable range; at 45 degrees, most of the grid fell within the field of view; and at 90 degrees, users on paths near the sensor axis remained visible over long distances while the outermost lateral paths were partly outside the view. Observations during data collection also showed that a distant user could remain visible in the thermal image without generating a presence output. These findings are consistent with literature describing thermal detection as dependent on target representation, thermal contrast, viewing geometry, and image analytics rather than visibility alone. For applications requiring long advance detection, thermal imaging is therefore promising, but the usable width and depth of the detection zone should be verified at the intended mounting geometry.

Hybrid-OR sensor also provided long advance reach, but with less variation in the outer boundary across the common orientations (approximately 93-99 ft). Because OR logic permits either sensing pathway to qualify the target, the two modalities may provide complementary opportunities for long-distance activation; the study did not record the individual channel

outputs, so this compensation cannot be confirmed directly. The same hardware operated in AND logic, where both PIR and microwave need to agree on detection, produced a much shorter practical range, showing that fusion logic can materially change the effective footprint of a hybrid technology even when the physical sensing hardware is unchanged. For lighting systems that prioritize early activation, permissive fusion is therefore more compatible with advance detection than restrictive confirmation logic.

LiDAR provided a shorter maximum range than the longest thermal and Hybrid-OR conditions, but its outer boundary remained nearly unchanged across orientation (approximately 81-85 ft). The tested implementation used active time-of-flight ranging within a thin horizontal 2D scan plane, with the minimum target-width criterion set to its lowest available value. The stable outer boundary is consistent with direct range measurement: once a sufficiently reflective portion of the user intersected the scan plane, the sensor could estimate position without relying on thermal contrast. Both LiDAR and thermal imaging allowed the monitored area to be restricted through software, but the underlying spatial representation differed. Thermal zones were defined within a two-dimensional image, whereas the tested LiDAR defined occupancy by range and angle within a physical scan plane. LiDAR is therefore attractive where a sharply bounded activation area is useful, although a single scan plane can be shadowed by a nearer user and should be evaluated for multi-user occlusion at crowded locations.

PIR produced shorter-to-moderate reach but offered useful control over coverage through the optical pattern. The broad circular PIR maintained a relatively uniform footprint as the sensor was rotated, whereas the corridor lens varied much more because it concentrated its Fresnel zones along a defined path. The outward/downward PIR configuration extended farther along a selected direction than the luminaire-mounted downward patterns. These results are consistent with literature showing that PIR range and coverage are governed by lens pattern, mounting geometry, thermal contrast, and how target trajectories intersect the Fresnel zones (Davis et al., 2022; Mukhopadhyay et al., 2018; Yun & Lee, 2014). The practical implication is not that one PIR pattern is inherently better: broad optics are better suited to localized multidirectional areas, corridor optics to known linear paths, and outward-facing optics to directional advance detection.

Overall, the range and coverage findings indicate three different spatial strategies for lighting control. Thermal imaging and Hybrid-OR are stronger candidates when long advance detection is needed; planar LiDAR is useful when direct spatial zoning and a well-defined boundary are important; and PIR is attractive when a simpler optical footprint can be deliberately matched to a local area or predictable path. Hybrid-AND logic should be considered cautiously when maximizing legitimate-user coverage is the primary objective.

DETECTION CONSISTENCY WITHIN THE PRACTICAL RANGE

The range comparison did not predict how consistently the technologies responded within their own practical boundaries. LiDAR had the highest overall position-based detection rate (approximately 71%), while Hybrid-OR, broad circular PIR, and thermal imaging were similar in

magnitude at approximately 55-56%. The outward/downward PIR configuration was lower at approximately 42%, the corridor PIR was approximately 27%, and Hybrid-AND logic was approximately 13%. Because the sample size was very large, all pairwise sensor comparisons were statistically significant; the more useful interpretation is the relative magnitude and the different spatial behaviors represented by these rates.

LiDAR combined the highest overall rate with only intermediate maximum reach. This is consistent with direct spatial ranging once a target intersects the configured scan plane. Thermal imaging showed the opposite range-consistency tradeoff: it produced the longest reach but only moderate overall detection consistency, consistent with image-based analytics requiring adequate target representation and qualification throughout the zone. Thus, LiDAR provided the strongest within-zone consistency when favorably aligned, whereas thermal imaging provided greater advance reach but required more careful verification of detection throughout the visible area.

PIR illustrates a different tradeoff. The broad circular pattern achieved moderate consistency over a shorter, more localized footprint, while the outward/downward configuration reached farther but was active at a smaller proportion of positions within that range. The corridor PIR performed poorly when evaluated across the broad multidirectional grid, but that result should be interpreted relative to its intended use: concentrating the sensing zones along a defined corridor reduces tolerance when the monitored area extends outside that corridor.

The hybrid comparison shows most clearly that processing logic can dominate within-range consistency. Hybrid-OR retained moderate-to-high responsiveness, whereas Hybrid-AND remained low even after positions outside its practical range were excluded. The AND penalty therefore was not limited to marginal long-distance detections; the more restrictive confirmation requirement reduced the frequency of controller-visible occupancy throughout the usable area. AND fusion may reduce nuisance activations, but false-positive performance was not evaluated, so the study cannot determine whether that benefit offsets the loss in legitimate-user response.

For lighting applications in which a single missed user could leave the area at a reduced light level - such as isolated crosswalks, low-volume paths, or pedestrian bridges - within-zone consistency may be more important than the absolute longest range. For high-volume multimodal facilities, consistency remains important but must be considered together with multi-user coverage and occlusion. The study therefore favors selecting a technology on the combination of usable range and within-zone reliability rather than on either metric alone.

INFLUENCE OF SENSOR ORIENTATION AND RELATIVE MOVEMENT

Orientation affected all of the evaluated technologies, indicating that orientation should be interpreted in relation to the physical detection mechanism.

For PIR, the literature indicates that detection depends on both the projected Fresnel-zone pattern and how a target moves through those zones. Movement across the pattern generally produces more zone transitions than movement directly toward or away from the sensor (Rafique &

Siddiqui, 2013; Yun & Lee, 2014). The present results did not show a simple lateral-versus-radial effect across the PIR configurations. The broad circular PIR and forward throw PIR maintained relatively similar detection rates across orientations, while its 0°, 45°, and 90° maximum ranges at 6 m mounting height differed by only about 4 ft. The corridor-pattern PIR behaved differently. Its detection rate varied substantially with orientation, with 0°, 45°, 135°, and 315° forming a higher-response group and 90°, 180°, 225°, and 270° forming a lower-response group. This pattern is consistent with the manufacturer-designed corridor footprint and with literature showing that PIR response depends on the alignment of the Fresnel zones with the target trajectory. However, the pattern does not follow simple lateral-to-radial progression. Taken together, the PIR results suggest that orientation sensitivity depends strongly on the optical pattern used to implement PIR sensing. Broad-area patterns were comparatively tolerant of changes in orientation under the tested geometry, whereas the corridor pattern required closer correspondence between the sensing footprint and the user path.

For hybrid sensing, OR logic maintained a similar maximum reach across 0°, 45°, and 90° but produced its highest detection rate at 45°. The 45° condition combined favorable forward coverage of the grid with oblique user movement, whereas 90° was primarily radial and 0° was lateral but less favorably positioned within the forward coverage. Hybrid-AND sensing showed the same general detection-rate advantage at 45 degrees, although its overall responsiveness remained much lower. The common trend across both fusion modes indicates that physical orientation and path geometry remained important even when the decision logic changed; using two sensing modalities did not remove the need for geometric commissioning.

Thermal imaging also produced its highest detection rate at 45 degrees, but the mechanism was different. Thermal imaging retains a two-dimensional spatial representation of the target, detection depends on the target's representation within the image and on the subsequent presence analytics rather than on crossing discrete zones. For data collection, the monitored area was configured for each orientation. However, defining a zone does not make detection uniform throughout that zone. As orientation changed, so did the portion of the grid visible to the sensor, the position of users within the image, their apparent size at distance, and the amount of time and image area over which they could be tracked. At 45 degrees, the approximately 95-degree field of view encompassed nearly the entire grid within the configured zone. The 0- and 90-degree detection rates were closer to each other, while their maximum distances differed substantially because the maximum reach was capped by test geometry in 0-degree orientation and the 90-degree view supported long travel along the sensor axis but did not include all lateral grid lines. Observations made during data collection support this interpretation. Distant users were sometimes visibly present near the edge of the thermal image without producing a detection output. In the 90° orientation, users moving along paths closely aligned with the sensor axis could also be detected farther away than users on adjacent parallel grid lines. This suggests that physical visibility within the thermal image was necessary but not always sufficient for the presence analytics to qualify the target. The long reach observed along the sensor axis may have

benefited from the user remaining continuously represented within a similar portion of the image as the user approached or receded, whereas the oblique 45° geometry maintained broad coverage of the grid while still providing substantial target displacement within the image. These mechanisms are plausible but were not independently manipulated, so the individual effects of image position, apparent target size, thermal contrast, and tracking behavior cannot be separated.

Similar to the thermal and hybrid configurations, the tested LiDAR produced its highest detection rate at 45°, but its maximum range remained nearly unchanged across orientations. The much larger rate changes—approximately 48% at 0 degrees, 95% at 45 degrees, and 52% at 90 degrees—therefore points to spatial overlap between the planar detection area and the experimental grid rather than a preference for oblique target movement. For planar LiDAR, commissioning should focus on how the scan plane and configured zone intersect all expected user paths. The strong 45-degree result is specific to the tested geometry and should not be treated as a general LiDAR mounting recommendation.

Taken together, the orientation results show why manufacturer field-of-view diagrams alone are insufficient. PIR requires attention to optical zones and expected trajectories; hybrid sensing retains those geometric requirements despite multimodal fusion; thermal imaging requires the required area to be well represented within the image and analytics zone; and planar LiDAR requires the scan plane and digital zone to intersect the monitored space appropriately. Orientation should therefore be verified with representative approach paths for the specific technology used.

ROAD-USER TYPE AND TARGET CHARACTERISTICS

Road-user type affected all of the technologies, but the pattern depended on what physical target information each technology used. LiDAR ranged from approximately 62% for bicycles to 76% for wheelchair users, while thermal imaging ranged from approximately 53% for pedestrians to 66% for wheelchair users. Several PIR configurations responded most strongly to bicycles, and Hybrid-AND sensing was particularly weak for wheelchair users. These differences indicate that a sensor validated only with walking pedestrians may not provide equivalent performance for a multimodal facility.

For the tested planar LiDAR, wheelchair users and pedestrians were detected more consistently than bicycles. This is consistent with a fixed horizontal-scan plane intersecting different target cross-sections: a pedestrian or seated wheelchair user can present a relatively continuous profile at the selected scan height, while a bicycle-rider assembly can contain narrow or discontinuous features. The low target-width setting reduced one threshold limitation but could not eliminate differences in profile continuity or time within the plane. A multilayer or 3D LiDAR would be less dependent on a single cross-section, although that architecture was not evaluated here.

Thermal imaging also performed relatively well across the three road-user groups because the technology retains a two-dimensional thermal profile rather than sampling only one horizontal

plane. Target area, thermal contrast, posture, speed, trajectory, and persistence across successive frames can all influence analytics. The observed road-user differences therefore support thermal imaging as a multimodal option, but they do not establish an inherent preference for a specific user type because these factors were not varied independently.

PIR produced a different pattern, with bicycles having the highest rates for several configurations. Faster bicycle movement may have generated more frequent transitions through Fresnel zones, and output hold time may have extended the active signal across additional sampled positions. However, the effect was not uniform across all configurations, reinforcing that user speed and profile interact with the specific lens pattern and processing. Hybrid-OR sensing was more responsive across user types than Hybrid-AND sensing, while the very low wheelchair response under AND logic is consistent with the stricter requirement for simultaneous qualification of the user's movement.

For crosswalks, shared-use paths, transit areas, and other multimodal facilities, the results provide stronger support for technologies that retained useful performance across all three tested road-user profiles, particularly thermal imaging and well-aligned LiDAR, with Hybrid-OR sensing as another option where advance reach is important. PIR remains practical for simpler or lower-cost applications, but commissioning should include the actual mix of pedestrians, bicycles, wheelchair users, and other mobility devices expected at the site.

INSTALLATION CONFIGURATION AND PROCESSING EFFECT

The results show that installation and processing can change technology performance enough to affect application suitability. Mounting height altered the ground projection of PIR zones, changed the image geometry of thermal sensing, and would determine what portion of a target intersects a planar LiDAR scan. Fusion logic and output timing further changed the controller-visible response without changing the underlying sensing hardware.

For the two downward-facing PIR patterns, increasing mounting height improved detection rate, particularly for the corridor lens, without a corresponding increase in maximum range. This is consistent with the manufacturer coverage diagrams and indicates that height changed how the Fresnel pattern intersected the grid rather than simply extending reach. PIR should therefore be selected and commissioned at the intended pole height; a lens that matches the lighting footprint at one height may not do so at another.

For thermal imaging, greater mounting height can expand the visible ground area while reducing the number of pixels representing a distant target. The tested 6-m condition reached farther at 90 degrees but had a lower detection rate than the 3-m condition; because the height comparison was not fully crossed with orientation, this should be treated as a possible reach-versus-target-representation tradeoff rather than an independent height effect. Thermal mounting should balance desired footprint width and advance distance against adequate target representation across the zone.

For planar LiDAR, scan height was not varied, but it is fundamental to the sensing geometry because it determines which parts of pedestrians, wheelchair users, and bicycles intersect the plane. A scan positioned too high or too low can miss relevant target profiles or increase interaction with clutter. The literature similarly reports missed targets when narrow horizontal laser planes do not intersect the intended road user (UC Davis California Lighting Technology Center & HNEI, 2021). For outward-facing PIR, mounting stability is an additional consideration because motion of the sensor itself can alter the apparent infrared pattern; rigid mounting is therefore important in exposed pole applications.

Processing settings also require explicit commissioning. The comparison between hybrid sensing logic demonstrated that fusion logic can change range and detection consistency substantially using the same hardware. Thermal and LiDAR systems can use software zones and masks to exclude areas where activation is not desired, while PIR coverage can be shaped through lens selection, aiming, sensitivity, or physical masking. Output hold or persistence settings can also extend the controller-visible active state after the initial sensing event. These parameters should be documented as part of the installed sensing configuration rather than treated as secondary device settings.

ENVIRONMENT AND OPERATIONAL CONSIDERATIONS

The temperature results were less conclusive than the geometry and road-user effects. Ambient and pavement-surface temperature were statistically associated with detection rate, but the direction of the descriptive trends varied among configurations. Because temperature was observational and actual target-to-background thermal contrast was not measured, the results do not support a causal temperature ranking among technologies.

The literature nevertheless indicates different environmental sensitivities. PIR depends on changes in long-wave infrared radiation, so reduced target-to-background thermal contrast can weaken the signal and changing thermal backgrounds or moving vegetation can produce unwanted response. Thermal imaging also depends on thermal contrast, but it retains spatial information that can support shape and tracking; reduced contrast still limits the information available to the analytics. The study's temperature trends therefore should not be interpreted as evidence that warmer pavement inherently improves or reduces either technology (Davis et al., 2022; Yun & Lee, 2014).

LiDAR and microwave sensing do not depend on target-to-background thermal contrast, but they have different environmental limitations. LiDAR relies on an optical path and can be affected by rain, fog, snow, dust, or other particles through attenuation or spurious returns. Microwave sensing is comparatively insensitive to visible illumination and thermal contrast but can be affected by clutter, multipath, moving vegetation, and precipitation depending on frequency and processing. These weather-related comparisons are literature-based because severe weather was not systematically evaluated in this study.

For practitioners, environmental selection should therefore be based on the dominant site challenge rather than a general claim of weather immunity. Thermal/PIR performance should be verified where seasonal thermal contrast may become small; LiDAR should be evaluated where optical visibility is frequently degraded; and microwave-based sensing may be advantageous where darkness or optical visibility is the primary concern, while still requiring control of clutter and nuisance response.

IMPLICATIONS FOR OUTDOOR LIGHTING APPLICATIONS

The findings do not support one preferred sensing technology for all outdoor lighting. Instead, the appropriate choice depends on the spatial control objective, expected road users, required advance distance, consequences of a missed detection, tolerance for nuisance activation, environmental exposure, and the degree of commission available at the site.

A central design objective should be to compare the commissioned detection footprint with the lighting footprint and the required lead-ahead distance. If the sensor footprint is smaller than the area that must be illuminated before the user arrives, increasing the luminaire hold time will not solve the initial late-activation problem. More appropriate options include re-aiming or changing mounting height, selecting a different PIR optic, using thermal or LiDAR zoning from a more favorable viewpoint, adding overlapping or upstream sensors, or networking adjacent luminaires so that detection at one location raises the output of the next lighting zone before the user enters it. Conversely, if the sensing footprint extends well beyond the desired lighting area, thermal and LiDAR software zones/masks, PIR optical masking or corridor lenses, sensitivity adjustment, or directional aiming can be used to reduce unnecessary activation. This footprint-matching approach is especially important where adaptive control is intended to reduce energy use, light trespass, skyglow, or luminaire operating time.

For busy crosswalks and multimodal intersections, thermal imaging and LiDAR are strong candidates because both can define software-based detection areas while retaining useful performance across pedestrians, bicycles, and wheelchair users. Thermal imaging provided greater advance reach and a two-dimensional view of the scene, but its detection output varied with how the full crossing was represented within the image. Planar LiDAR provided the highest within-range consistency when favorably aligned and directly bounded the monitored area, but scan-plane occlusion should be considered where several users may occupy the crossing at once. Hybrid-OR sensing can provide long advance detection, but nuisance-activation performance should be verified before using permissive logic in complex traffic environments.

For low-volume rural crosswalks or isolated pedestrian approaches, the priority is often reliable activation for a single user rather than broad classification capability. Well-aligned LiDAR or thermal imaging can provide strong advance detection where the consequences of a miss are high. Where cost and complexity are stronger constraints and the approach is predictable, PIR can also be effective if its footprint is placed sufficiently upstream or linked to neighboring

luminaires for lead-ahead activation. Hybrid-AND sensing is less attractive for this purpose based on its low legitimate-user response unless nuisance rejection is a dominant requirement.

For sidewalks, trails, cycleways, pedestrian bridges, and tunnel walkways, predictable linear movement favors corridor PIR when the lens can be aligned with the path. Broad PIR is more appropriate at trail junctions, plazas, or local nodes with multidirectional approaches. Thermal imaging or LiDAR becomes more useful when the path requires longer advance detection, software-defined exclusion zones, or coverage of more complex geometry.

For parking lots, plazas, and other area-lighting applications, broad local PIR can be effective where pole spacing is tight, and each sensor only needs to cover the nearby lighting zone. Where the lighting footprint extends beyond the reliable PIR footprint, overlapping sensors or networked luminaire activation are preferable to assuming one luminaire-mounted sensor covers the full photometric area. Larger or more complex sites may justify thermal imaging, LiDAR, or radar-based approaches to obtain earlier or more spatially controlled activation across several aisles or zones. Prior parking-lot evaluations similarly found that incomplete sensor coverage can leave substantial portions of the lighting area without reliable occupancy response (Kinze et al., 2012).

For covered parking, underpasses, entrances, and building-adjacent areas, outward/downward PIR offers a relatively simple option for local and moderate advance detection when mounted rigidly and aimed across expected movement. Thermal imaging or LiDAR is more appropriate when the monitored area is larger, requires software-defined exclusion zones, or includes several distinct approach paths.

For city streets and intersections where vulnerable-road-user detection is the primary control need, the longer advance reach of thermal imaging and Hyb-OR can be advantageous. For highways and higher-speed vehicle-oriented approaches, the literature strongly supports purpose-designed radar or traffic LiDAR because range, velocity, and longer approach distance become important. Standalone radar was not evaluated in this study, and the vehicle trials were excluded from the final spatial analysis, so these vehicle-oriented recommendations should be treated as literature-based rather than direct experimental findings.

For parks, dark-sky sensitive sites, and environmentally sensitive areas, matching the sensing footprint closely to the intended lit path can be more important than maximizing range. Corridor PIR offers a simple way to constrain activation along a known route; thermal imaging and LiDAR provide software-defined zones where more precise spatial control is needed. These approaches can support lower unoccupied light levels and reduce spill into adjacent areas, but nuisance response to wildlife or environmental motion should be evaluated because false-positive performance was outside the scope of this study.

Table 18 summarizes how the tested sensing approaches translate to representative outdoor-lighting applications. The classifications are intended as application guidance based on the present findings and reviewed literature rather than universal technology rankings.

Table 18. Comparative strengths, considerations, and representative outdoor-lighting applications of the evaluated sensing approaches.

Sensing approach	Principal strengths for lighting control	Important considerations	Applications where it may be particularly useful
Broad-pattern PIR	Simple occupancy trigger; broad local coverage; relatively tolerant of multidirectional approaches; readily integrated with luminaires	Fresnel-zone crossing, thermal contrast, mounting height, and output timing influence response	Local street/area lighting, plazas, parking areas, trail nodes, campus paths
Corridor-pattern PIR	Concentrates sensing along a defined path; simple and relatively low-complexity implementation	Stronger dependence on path alignment, mounting height, and movement through Fresnel zones	Sidewalks, cycleways, pedestrian bridges, trails, tunnel walkways
Outward/downward PIR	Moderate advance reach combined with local downward coverage	Requires appropriate aim; transverse movement generally favored; thermal/background disturbances can produce nuisance activation	Covered parking, entrances, building perimeter, localized parking/area lighting
Hybrid-OR: PIR + microwave	Long advance reach; either sensing channel can qualify detection; comparatively responsive	Potential nuisance-activation tradeoff was not evaluated; performance depends on both sensing channels and processing	Road approaches, crosswalk approaches, intersections, larger directional areas where early activation is important
Hybrid-AND: PIR + microwave	More restrictive dual-channel confirmation may support nuisance rejection	Substantially reduced detection rate and range in this study; nuisance-rejection benefit not quantified	Applications where confirmation is prioritized over maximum sensitivity; not preferred from the present results when reliable VRU activation is the primary objective
Thermal imaging	Long advance detection; configurable zones; detects in darkness and is not dependent on visible illumination; relatively strong response across tested road users	Detection depends on target representation, thermal scene, viewing geometry, zone placement, and analytics	Crosswalks, intersections, roadway approaches, large parking areas, multimodal pedestrian facilities
2D planar LiDAR	Highest overall detection consistency in this study; precise spatial zoning; active ranging does not depend on thermal contrast	Scan height, zone alignment, target profile, and occlusion must be considered	Crosswalks, pedestrian refuges, defined entrances, pedestrian bridges, controlled activation zones

Standalone radar*	Long-range motion/velocity capability and comparatively strong performance in reduced visibility	Antenna pattern, clutter, multipath, processing, and target motion affect performance	Highways, roadway approaches, intersections, large parking areas, vehicle-oriented applications
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*Standalone radar was reviewed in the literature but was not directly evaluated as an independent sensor in this study.

Overall, the study supports selecting sensors by the required sensing task and control geometry rather than by nominal range or technology label alone. Thermal imaging offers long advance reach and flexible image-based zoning but requires careful viewing geometry and verification throughout the defined zone. Planar LiDAR offers direct spatial ranging and high consistency when well aligned, but scan height and occlusion constrain its use. PIR remains attractive for simpler, lower-cost local or corridor applications when the optics and mounting are matched to the path. Hybrid PIR-microwave sensing can provide either broad responsiveness or restrictive confirmation depending on the fusion logic. In all cases, field commissioning should verify the actual detection footprint against the lighting footprint, expected user paths, and required lead-ahead distance before the control strategy is finalized.

LIMITATIONS

Several limitations should be considered when interpreting the findings. First, the study evaluated specific commercial products and configurations; only one LiDAR, thermal-imaging, and dual-technology sensor was tested. The results therefore describe the tested configurations rather than the broader sensing technologies.

The controlled test grid provided consistent comparison conditions but did not represent the full range of roadway geometries, mounting locations, traffic patterns, weather, or seasonal conditions encountered in practice. Mounting height and orientation were also not fully crossed for every sensor, and some conditions were unavailable because of data-quality limitations. Temperature was observed rather than controlled and covered a limited range, so the temperature trends should be considered exploratory.

As the detection rate was position-based, it should not be interpreted as the proportion of complete traversals successfully detected. Sensor output duration could also extend an active signal beyond the location of the initial detection. In addition, false-positive detections and detection latency were not evaluated. The study therefore cannot determine whether configurations with more restrictive detection, such as the Bosch DUAL in AND mode, provided a corresponding reduction in nuisance activations or whether sensors responded quickly enough for a specific lighting-control application.

Pedestrians, bicyclists, and wheelchair users were evaluated, but vehicle data were excluded because of GPS data-quality issues. User characteristics, speeds, and profiles were not independently controlled, and experimenter assignment was not fully balanced across all user

conditions. Accordingly, road-user differences should be interpreted as performance under the tested user configurations rather than isolated effects of user type.

CONCLUSION

This study demonstrated that outdoor occupancy-sensing performance cannot be characterized by sensing technology or maximum detection range alone. The technologies differed in their balance of detection range, spatial coverage, and consistency within the detectable area, and these differences were further influenced by sensor orientation, mounting geometry, road-user type, and processing configuration. Thermal imaging provided strong potential for long-range detection and flexible image-based zoning, while LiDAR provided comparatively consistent detection and direct spatial definition of the monitored area when the sensing geometry was appropriately aligned. PIR provided simpler local or path-oriented detection, but its performance depended strongly on optical pattern and its relationship with user movement. Hybrid PIR–microwave sensing showed that fusion logic can substantially change the performance of the same sensing architecture, with permissive and restrictive logic producing different tradeoffs between responsiveness and confirmation.

The findings also show that differences within a sensing technology can be substantial. PIR coverage changed with lens geometry and mounting conditions, while hybrid performance changed considerably with decision logic. Similarly, the performance of imaging and ranging technologies depended on how their fields of view, detection zones, or scan planes intersected the monitored area. Therefore, technology selection alone does not define field performance; the complete sensing configuration and its installation geometry determine how the underlying sensing principle translates to usable detection.

For adaptive street and area lighting, the most relevant measure is ultimately whether the sensing system provides sufficiently reliable detection at the locations needed to support the intended lighting response. This requires considering the sensing footprint together with the lighting footprint, expected road-user paths, and required advance activation distance. The results support using different sensing approaches for different spatial and operational requirements rather than identifying a universally preferred technology. They also reinforce the need to verify sensor performance under the intended mounting, orientation, user, and site conditions before deployment.

RECOMMENDATIONS

Based on the findings of this study, practitioners should select and configure occupancy sensing according to the required lighting-control function, rather than relying primarily on technology type, nominal field of view, or maximum detection range. The following recommendations are intended to support sensor selection, placement, and commissioning for street and area-lighting applications.

1. Define the required detection footprint from the lighting response before selecting the sensing technology.

Determine where a user should first be detected relative to the area requiring illumination, accounting for user travel speed and the time required for the lighting system to respond. The sensor should provide reliable detection before the user enters the area where the higher light level is needed.

2. Match the sensing footprint to the lighting footprint and expected travel paths.

Where the sensing footprint is smaller than the illuminated area, practitioners should consider changing sensor placement or orientation, using broader or overlapping sensing zones, adding upstream detection, or networking adjacent luminaires so that detection at one location activates lighting ahead of the user. Where sensing extends substantially beyond the intended lighting area, corridor optics, physical masking, or software-defined zones available with technologies such as thermal imaging and LiDAR can be used to reduce unnecessary activation.

3. Select the sensing approach according to the required spatial behavior.

Broad-pattern PIR is appropriate where relatively simple, localized, multidirectional occupancy detection is needed, while corridor-pattern PIR is better suited to defined pedestrian or bicycle paths where the sensing pattern can be aligned with travel. Thermal imaging should be considered where broader coverage, longer advance detection, multimodal-user detection, and configurable spatial zones are important. LiDAR is particularly useful where a clearly defined physical detection area is required, although planar systems should be positioned to maintain target intersection and minimize occlusion. Hybrid PIR–microwave sensing can provide longer or more robust detection, but the fusion logic should be selected according to the intended control objective.

4. Treat mounting height, orientation, optics, and software configuration as part of sensor selection.

Mounting height, orientation, optics, sensitivity, and processing settings can substantially change detection performance. PIR systems should be installed using lens patterns and orientations appropriate to expected user movement; thermal-imaging systems should be positioned to maintain adequate target representation throughout the monitored area; and planar LiDAR should be mounted so the scan plane reliably intersects the intended road-user profiles.

5. Commission sensors using representative users and movement paths.

Field verification should include pedestrians, bicyclists, wheelchair users, and other mobility types expected at the site, using realistic approach directions rather than a single walking path. For multimodal facilities such as crosswalks and shared-use paths, acceptable performance should be demonstrated across the full intended detection area, not only along the sensor centerline or at the maximum detection distance.

6. Select detection logic according to the consequence of missed and unwanted activation.

More permissive sensing or fusion logic is preferable where missed detection could leave a legitimate user approaching under reduced lighting, particularly at low-volume crossings or isolated pedestrian facilities. More restrictive confirmation logic may be appropriate where nuisance activation is a greater concern, but practitioners should verify that the resulting reduction in legitimate-user detection remains acceptable. Both missed detections and unwanted activations should therefore be evaluated during commissioning.

7. Verify performance under the environmental conditions expected at the site.

PIR and thermal installations should be checked under representative seasonal thermal conditions, while LiDAR installations should consider precipitation, fog, snow, dust, and optical-path obstruction. Microwave- or radar-based systems should be evaluated for clutter, vegetation, multipath, and surrounding traffic.

For larger or more complex lighting systems, practitioners should also consider coordinated sensing rather than requiring each sensor to independently cover the entire illuminated area. Overlapping detection zones, communication between neighboring luminaires, and upstream activation can provide timely illumination while allowing lower unoccupied light levels. This approach is particularly useful where the goals include reducing energy use, light trespass, skyglow, and unnecessary operating time without compromising detection of approaching users.

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APPENDIX A

SELECTED SENSOR SPECIFICATIONS AND SENSING ARCHITECTURE

This appendix summarizes the manufacturer-reported specifications and sensing architecture of the sensors selected for evaluation. Brief study-configuration notes identify the implementation tested. Manufacturer coverage values are nominal and should not be interpreted as equivalent to the measured study range or coverage.

1. TE Connectivity LUMAWISE Motion - Circular PIR

Key specifications:

- LMLO circular configuration, PN 1-2445583-1; dual-sensor PIR with ambient-light sensing and environmentally reactive sensitivity.
- Nominal footprint: 30 x 24 m at 5 m; 32 x 34 m at 8 m; 28 x 28 m at 12 m mounting height.
- IP66, IK07; operating temperature -40°C to 65°C; logic-level motion output with 1-s minimum pulse width.

Sensing architecture:

- Downward-facing luminaire-integrated PIR with a broad circular Fresnel-lens pattern that distributes detection zones around the mounting location (Figure 17).
- Requires an external lighting controller; temperature-responsive logic modifies motion-output behavior under high onboard temperature.

Study configuration

- Mounted downward-facing and evaluated at 6 and 12 m while rotated relative to the fixed grid.



Figure 17. LUMAWISE Motion circular-pattern PIR sensor.

2. TE Connectivity LUMAWISE Motion - Rectangular PIR

Key specifications:

- LMLO rectangular configuration, PN 2445583-1; same sensing electronics and environmental ratings as the circular configuration.

- Nominal footprint: 30 x 6 m at 5 m; 30 x 10 m at 8 m; 36 x 12 m at 12 m mounting height.

Sensing architecture:

- Uses the same dual-sensor PIR platform as the circular version, but a corridor-oriented Fresnel lens concentrates the detection zones along a linear path (Figure 18).

Study configuration

- Mounted downward-facing and evaluated at 6 and 12 m using the same rotation framework as the circular configuration.



Figure 18. LUMAWISE Motion rectangular-pattern PIR sensor.

3. RAB STL360 PIR

Key specifications:

- Outdoor PIR with nominal 180° forward coverage to approximately 60 ft plus 360° downward/side coverage.
- Recommended mounting height for maximum range: 6-10 ft; sensitivity adjustable approximately 30%-100%; output time approximately 5 s-12 min.
- 120 V AC, approximately 1 W; suitable for wet locations; automatic temperature compensation and physical lens masking.

Sensing architecture:

- Combines a long-range forward PIR region with a separate downward/side PIR region (Figure 19). Detection is based on motion-induced infrared changes through the segmented optical pattern.

Study configuration:

- Mounted approximately 6 ft above the pavement, level from side to side, with medium sensitivity and a 5-s Test Mode output.



Figure 19. RAB STL360 PIR sensor and adjustment controls.

4. Bosch OD850-F1 Hybrid PIR-Microwave Sensor

Key specifications:

- Hybrid PIR + 10.525-GHz microwave sensing; nominal broad coverage approximately 15 x 15 m (50 x 50 ft).
- PIR processing: Motion Analyzer II; microwave processing: Linear Travel Distance (LTD).
- Selectable fusion: OR mode accepts either sensing input; AND mode requires simultaneous PIR and microwave qualification.
- IP54; operating temperature -40°C to 54°C; weather- and vandal-resistant polycarbonate enclosure (Figure 20).

Sensing architecture:

- The PIR and microwave subsystems monitor the same general area but process different motion information; a selectable output-stage fusion rule combines their decisions.

Study configuration:

- The same outward-facing unit was evaluated at 3 m in OR (Hyb-OR) and AND (Hyb-AND) modes with physical hardware and mounting held constant.



Figure 20. Bosch OD850-F1 hybrid PIR-microwave sensor.

5. Teledyne FLIR TrafiOne 195 Thermal-Imaging Sensor

Key specifications:

- 160 x 120-pixel uncooled VOx focal-plane-array microbolometer; 8-14 μm LWIR; 9 frames/s; 95° horizontal field of view.
- Manufacturer-reported pedestrian/bicycle presence distance: 0-12 m; specified installation height: 3.5-6 m.
- Up to eight pedestrian-presence and eight vehicle-presence zones; software configuration of detection zones and masks.
- Aluminum housing, PC GF10 sunshield, PA GF30 mounting clamps and aluminum tube (Figure 21); IP67; operating temperature -40°C to 60°C.

Sensing architecture:

- Forms a two-dimensional thermal image and applies presence analytics within software-defined regions rather than producing a direct binary response from a single infrared element.

Study configuration:

- Evaluated at 3 and 6 m. Manufacturer-guided initial aiming did not reproduce the indicated coverage in the test grid; preliminary alignment trials established an aim of approximately 15° below horizontal, with a grid-matched pedestrian zone defined for each orientation.



Figure 21. TrafiOne 195 sensor (left) and example software-defined thermal detection zone (right).

6. OPTEX REDSCAN RLS-2020S LiDAR Sensor

Key specifications:

- Class 1 infrared laser scanning with time-of-flight ranging.
- Standard detection area approximately 20 x 20 m across a 95° scan; specified radial range approximately 1-21 m for a 10%-reflectivity target.
- Detection resolution 0.25°; response setting approximately 75 ms to 1 min in indoor/outdoor modes; alarm period approximately 2 s.
- Indoor/outdoor model (Figure 22); IP66; operating temperature -40°C to 60°C; software-defined detection areas within the scan geometry.

Sensing architecture:

- Repeated range measurements across scan angle form a two-dimensional planar map. In horizontal mode, detection occurs within a thin physical scan plane and target position is represented by range and scan angle.

Study configuration

- Mounted with the scan plane approximately 1.2 m above and parallel to the pavement; Outdoor Mode, medium sensitivity, environmental-resistance processing, standard range, and approximately 10-mm minimum target width were used.



Figure 22. OPTEX REDSCAN RLS-2020S LiDAR sensor.

APPENDIX B

This appendix provides the detailed experimental test matrices used for the sensor evaluation. Each table specifies the sensor, user type, sensor orientation angle, repetition count, and mounting height used for each test condition.

Table 19. Detection range and coverage assessment

Technology	Sensor	User	Steps	Repetitions	Mount height
PIR	Lumawise Circle	Pedestrian	0°	3	6m
			45°	3	
			90°	3	
			135°	1	
			180°	1	
			225°	1	
			270°	1	
			315°	1	
		Bicycle	0°	1	
			90°	1	
		Wheelchair	0°	1	
			90°	1	
		Car	0°	1	
			90°	1	
	Lumawise Rectangle	Pedestrian	0°	3	6m
			45°	3	
			90°	3	
			135°	1	
			180°	1	
			225°	1	
			270°	1	
			315°	1	
		Bicycle	0°	1	
			90°	1	
		Wheelchair	0°	1	
			90°	1	
		Car	0°	1	
			90°	1	
	RAB	Pedestrian	0°	3	3m
			45°	1	
			90°	3	
			135°	1	
			180°	1	
			225°	1	

Technology	Sensor	User	Steps	Repetitions	Mount height
			270°	1	
			315°	1	
		Bicycle	0°	1	
			45°	1	
			90°	1	
		Wheelchair	0°	1	
			90°	1	
		Car	0°	1	
			90°	1	
Hybrid -OR (PIR + Microwave)	Bosch Hybrid-OR	Pedestrian	0°	3	3m
			45°	1	
			90°	3	
		Bicycle	0°	1	
			45°	1	
			90°	1	
		Wheelchair	0°	1	
			45°	1	
		Car	0°	1	
			90°	1	
Hybrid - AND (PIR + Microwave)	Bosch Hybrid- AND	Pedestrian	0°	3	3m
			45°	1	
			90°	3	
		Bicycle	0°	1	
			45°	1	
			90°	1	
		Wheelchair	0°	1	
			90°	1	
		Car	0°	1	
			90°	1	
Thermal Imaging	TrafiOne	Pedestrian	0°	3	3m
			45°	3	
			90°	3	
		Bicycle	0°	1	
			45°	1	
			90°	1	
		Wheelchair	0°	1	
			45°	1	
			90°	1	
		Car	0°	1	
			45°	1	

Technology	Sensor	User	Steps	Repetitions	Mount height
			90°	1	
LiDAR	Optex America	Pedestrian	0°	3	1.8m
			45°	3	
			90°	3	
		Bicycle	0°	1	
			45°	1	
			90°	1	
		Wheelchair	0°	1	
			45°	1	
			90°	1	
		Car	0°	1	
			45°	1	
			90°	1	

Table 20. Mounting height assessment.

Sensor	User	Steps	Repetitions	Mount height
Lumawise rectangle	Pedestrian	0°	3	12m
		45°	1	
		90°	3	
	Bicycle	0°	1	
		45°	1	
		90°	1	
	Wheelchair	0°	1	
		45°	1	
		90°	1	
	Car	0°	1	
		90°	1	
Lumawise circle	Pedestrian	0°	3	12m
		45°	1	
		90°	3	
	Bicycle	0°	1	
		45°	1	
		90°	1	
	Wheelchair	0°	1	
		45°	1	
		90°	1	
	Car	0°	1	
		90°	1	
TrafiOne	Pedestrian	90°	3	6m
	Bicycle	90°	1	

APPENDIX C

CONFIGURATION SPECIFIC DETECTION RANGE

PIR-1 Range

The initial estimate for the minimum detection distance was 0.5 feet (std error = 0.04) and the initial estimate for the maximum detection distance was 72.4 feet (std error = 0.57), as shown in Table 21.

Table 21. Detection range estimates for PIR-1.

Sensor	Quantile	Estimate (ft)	Std Err	95% Lower Confidence Limit	95% Upper Confidence Limit	t Value	Pr> t
PIR-1	0.001	0.5	0.04	0.44	0.60	13.2	<.0001
	0.011*	3.46	0.01	3.43	3.48	266.1	<.0001
	0.987*	63.3	0.21	62.89	63.73	299.5	<.0001
	0.999	72.4	0.57	71.26	73.51	126.2	<.0001

Sparse detections at both tails resulted in accepted practical bounds of 3.5 ft (0.011 quantile) and 63.3 ft (0.987 quantile) (Figure 23). The accepted detection range was 3.5–63.3 ft.

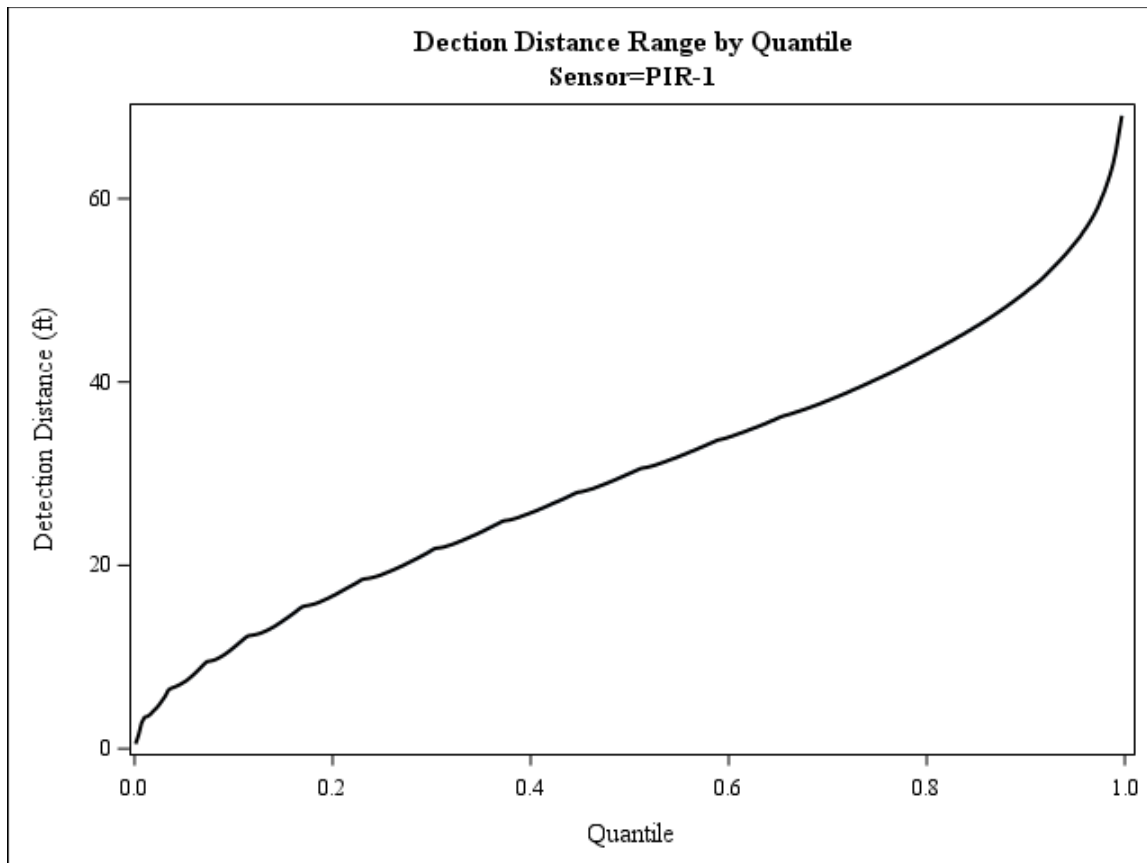


Figure 23. Graph. Detection distance by quantile for PIR-1 sensor.

PIR-2 Range

The initial estimate for the minimum detection distance was 0.5 feet (std error = 0.08) and the initial estimate for the maximum detection distance was 77.3 feet (std error = 0.30), as shown in Table 22.

Table 22. Detection range estimates for PIR-2.

Sensor	Quantile	Estimate (ft)	Std Err	95% Lower Confidence Limit	95% Upper Confidence Limit	t Value	Pr> t
PIR-2	0.001	0.5	0.08	0.34	0.65	6.3	<.0001
	0.013*	3.41	0.02	3.37	3.46	146.9	<.0001
	0.985*	58.66	0.54	57.59	59.73	107.7	<.0001
	0.999	77.3	0.30	76.71	77.88	258.8	<.0001

Review of both tails showed that detections below approximately 3.4 ft and beyond approximately 58.7 ft were sparse and surrounded primarily by non-detections (Figure 24). Therefore, 3.4 ft (0.013 quantile) and 58.7 ft (0.985 quantile) were accepted as the practical minimum and maximum detection distances, respectively. The accepted detection range for the PIR-2 sensor was 3.4–58.7 ft.

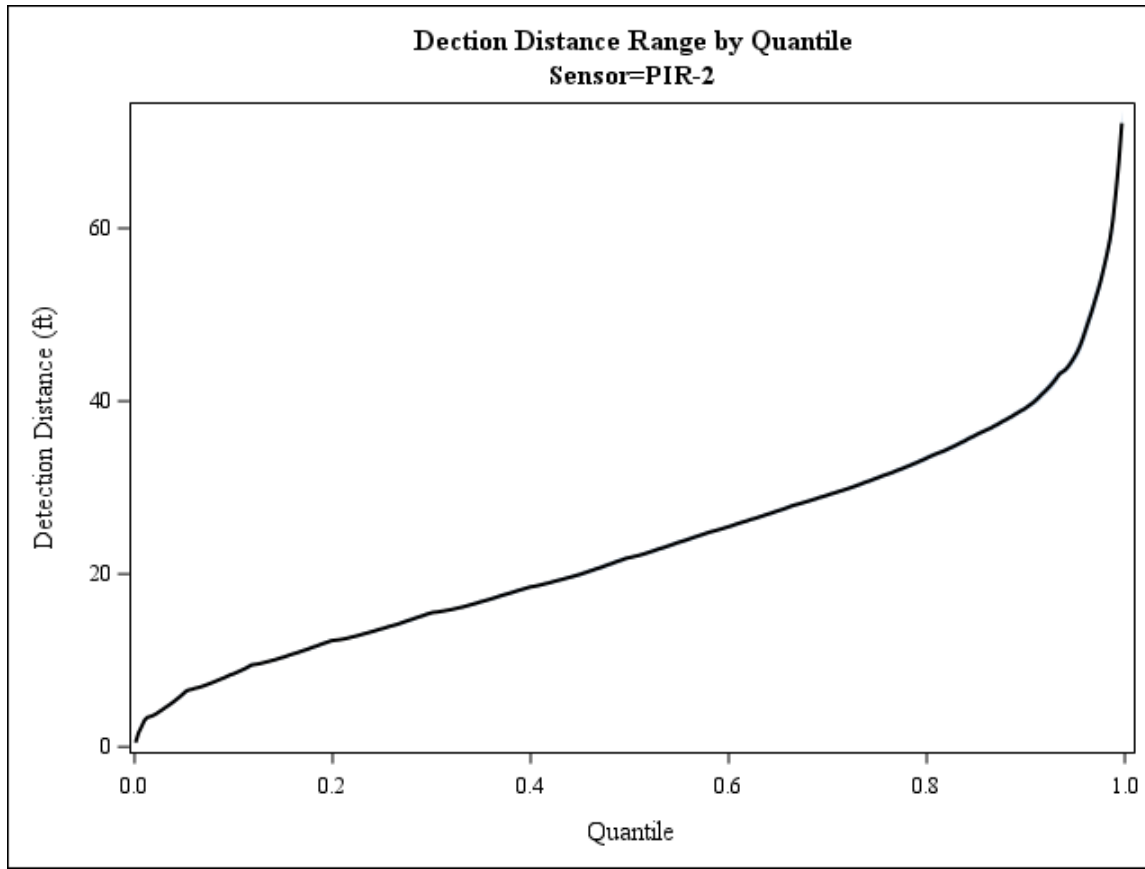


Figure 24. Graph. Detection distance by quantile for PIR-2 sensor.

PIR-3 Range

The initial estimate for the minimum detection distance was 1.1 feet (std error = 0.13) and the initial estimate for the maximum detection distance was 82.1 feet (std error = 0.52), as shown in Table 23.

Table 23. Detection range estimates for PIR-3.

Sensor	Quantile	Estimate (ft)	Std Err	95% Lower Confidence Limit	95% Upper Confidence Limit	t Value	Pr> t
PIR-3	0.001	1.1	0.13	0.82	1.34	8.1	<.0001
	0.009*	3.70	0.10	3.50	3.90	36.8	<.0001
	0.991*	74.17	0.38	73.43	74.92	193.9	<.0001
	0.999	82.1	0.52	81.10	83.15	157.0	<.0001

Review of both tails showed that detections below approximately 3.7 ft and beyond approximately 74.2 ft were sparse and surrounded primarily by non-detections (Figure 25). Therefore, 3.7 ft (0.009 quantile) and 74.2 ft (0.991 quantile) were accepted as the practical

minimum and maximum detection distances, respectively. The accepted detection range for the PIR-3 sensor was 3.7–74.2 ft.

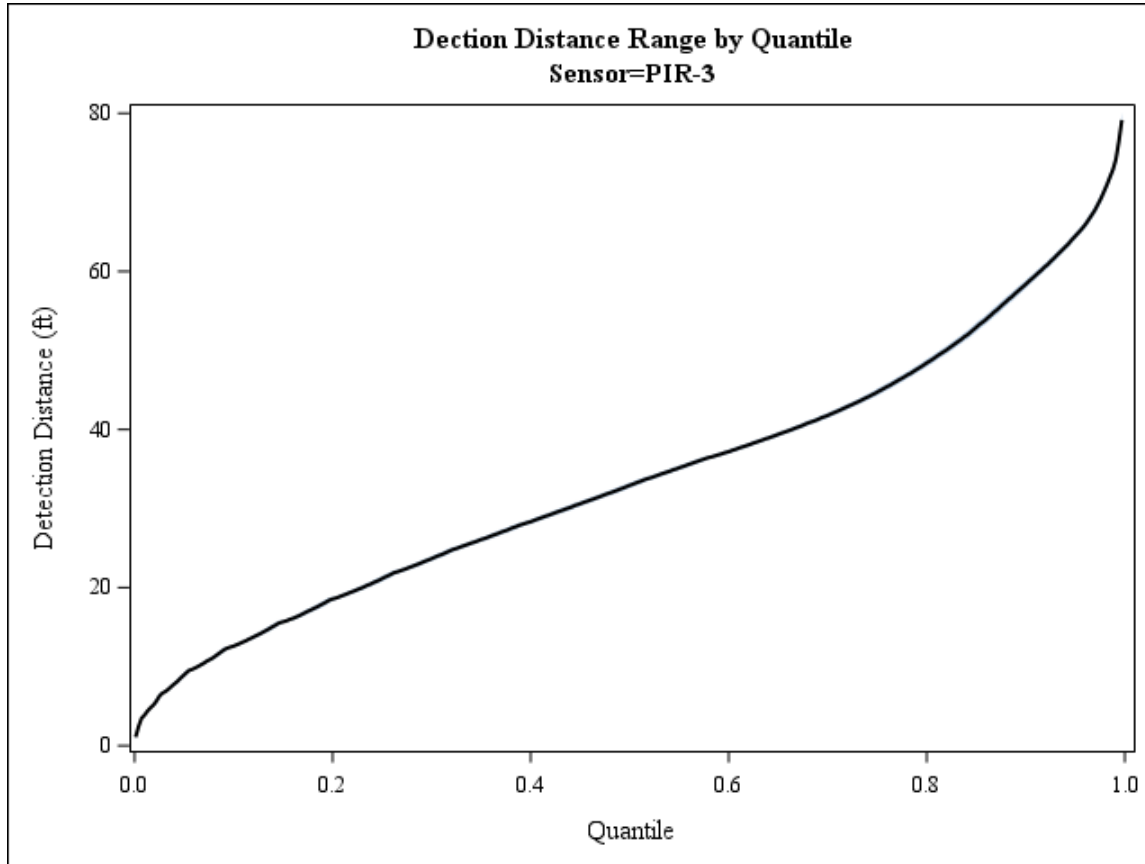


Figure 25. Graph. Detection distance by quantile for PIR-3 sensor.

Hybrid-OR Range

The initial estimate for the minimum detection distance was 1.40 feet (std error = 0.19) and the initial estimate for the maximum detection distance was 97.4 feet (std error = 0.18), as shown in Table 24.

Table 24. Detection range estimates for Hybrid-OR.

Sensor	Quantile	Estimate (ft)	Std Err	95% Lower Confidence Limit	95% Upper Confidence Limit	t Value	Pr> t
Hybr-OR	0.001	1.4	0.19	1.02	1.75	7.4	<.0001
	0.013*	6.73	0.05	6.64	6.82	146.1	<.0001
	0.999*	97.4	0.18	97.03	97.74	541.7	<.0001

Detections below approximately 6.7 ft were sparse and were surrounded primarily by non-detections; therefore, 6.7 ft (0.013 quantile) was accepted as the practical minimum (Figure 26). The accepted detection range was 6.7 feet – 97.4 feet.

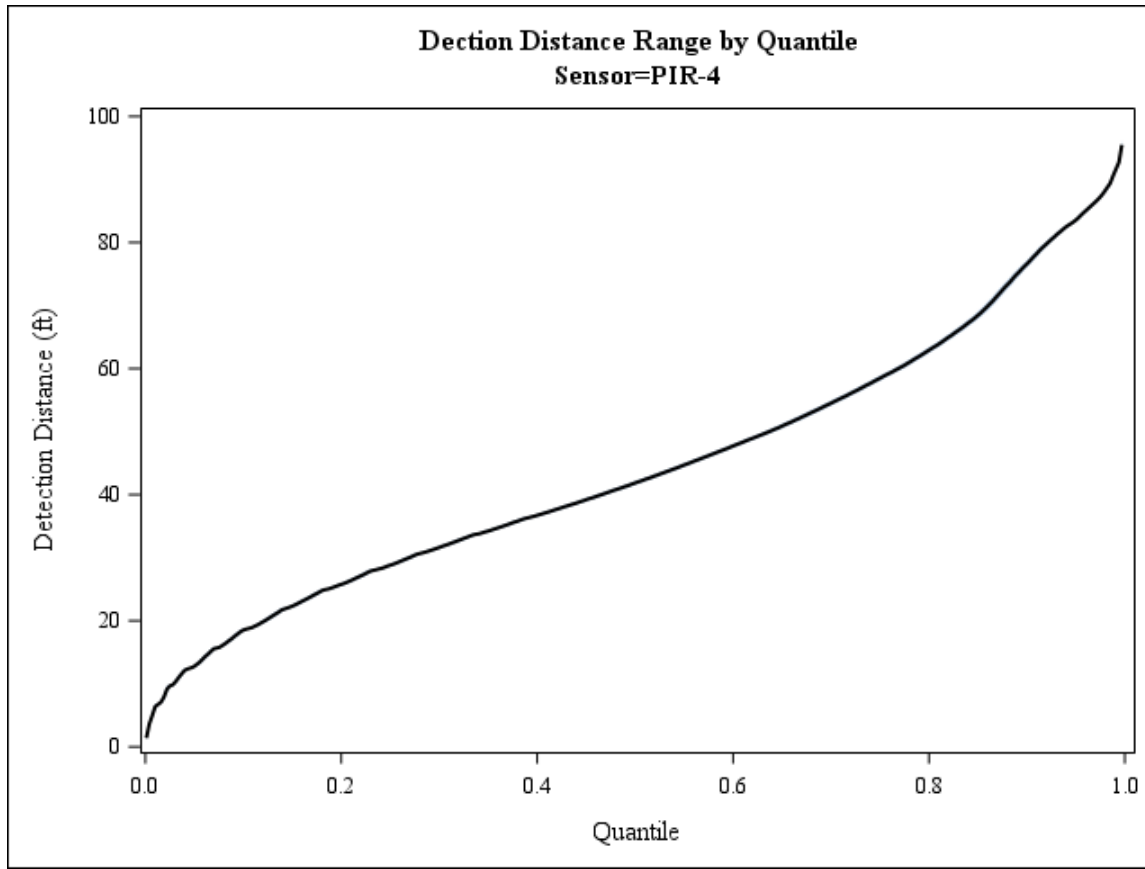


Figure 26. Graph. Detection distance by quantile for Hyb-OR sensor.

Hybrid-AND Range

The initial estimate for the minimum detection distance was 6.54 feet (std error = 0.01) and the initial estimate for the maximum detection distance was 74.8 feet (std error = 1.00), as shown in Table 25.

Table 25. Detection range estimates for Hyb-AND.

Sensor	Quantile	Estimate (ft)	Std Err	95% Lower Confidence Limit	95% Upper Confidence Limit	t Value	Pr> t
Hyb-AND	0.001*	6.54	0.01	6.53	6.55	1259.1	<.0001
	0.989*	64.89	0.60	63.72	66.08	107.79	<.0001
	0.999	74.8	1.00	72.81	76.73	74.8	<.0001

Review of the upper tail showed that detections beyond approximately 65 ft were sparse and were surrounded primarily by non-detections (Figure 27). The accepted practical maximum was therefore 64.9 ft (0.989 quantile). The detection range of the Hyb-AND, across the tested conditions was estimated at 6.5 feet – 65 feet.

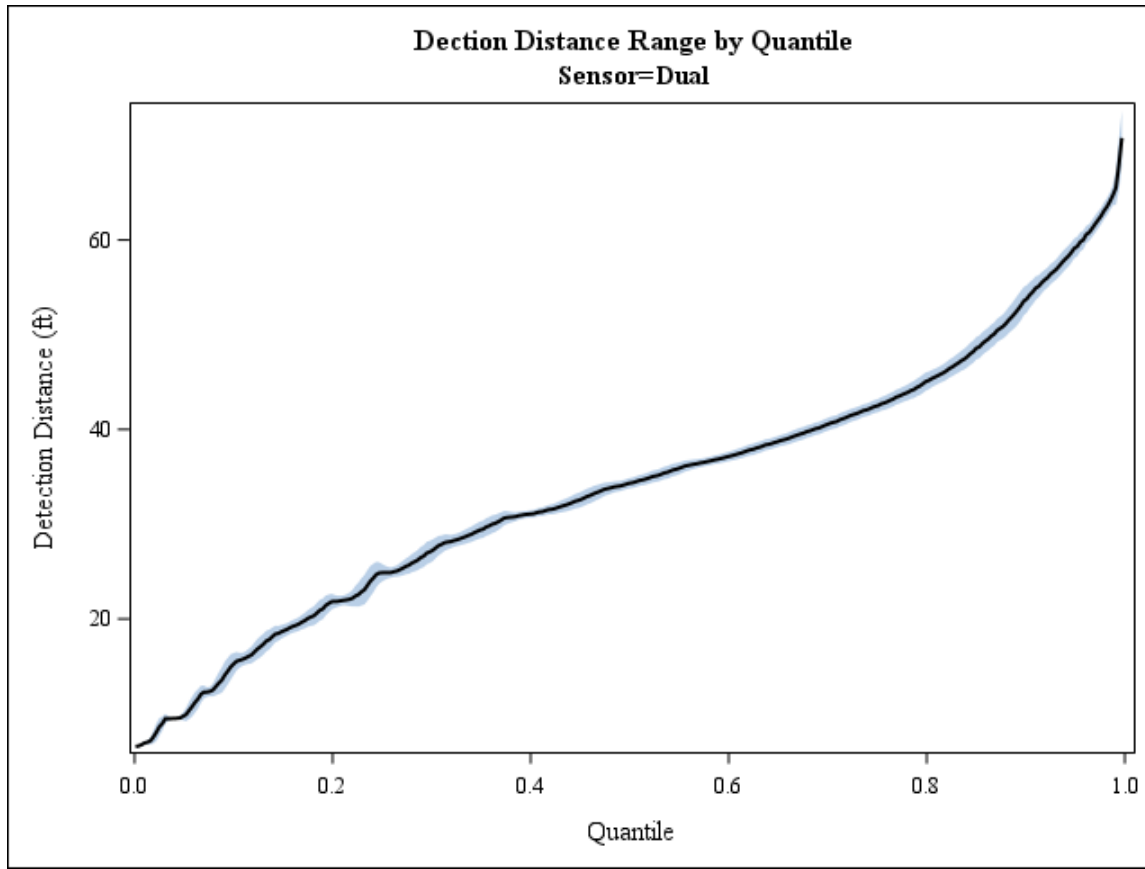


Figure 27. Graph. Detection distance by quantile for Hyb-AND sensor.

LiDAR Range

The initial estimate for the minimum detection distance was 0.7 feet (std error = 0.17) and the initial estimate for the maximum detection distance was 85.8 feet (std error = 0.23), as shown in Table 26.

Table 26. Detection range estimates for LiDAR.

Sensor	Quantile	Estimate (ft)	Std Err	95% Lower Confidence Limit	95% Upper Confidence Limit	t Value	Pr> t
LiDAR	0.001	0.7	0.17	0.41	1.07	4.4	<.0001
	0.005*	3.49	0.12	3.26	3.72	30.1	<.0001
	0.993*	82.04	0.23	81.58	82.50	349.6	<.0001
	0.999	85.8	0.23	85.39	86.29	373.3	<.0001

Review of both tails showed that detections below approximately 3.5 ft and beyond approximately 82.0 ft were sparse and surrounded primarily by non-detections (Figure 28). Therefore, 3.5 ft (0.005 quantile) and 82.0 ft (0.993 quantile) were accepted as the practical

minimum and maximum detection distances, respectively. The accepted detection range for the OPTEX was 3.5–82.0 ft.

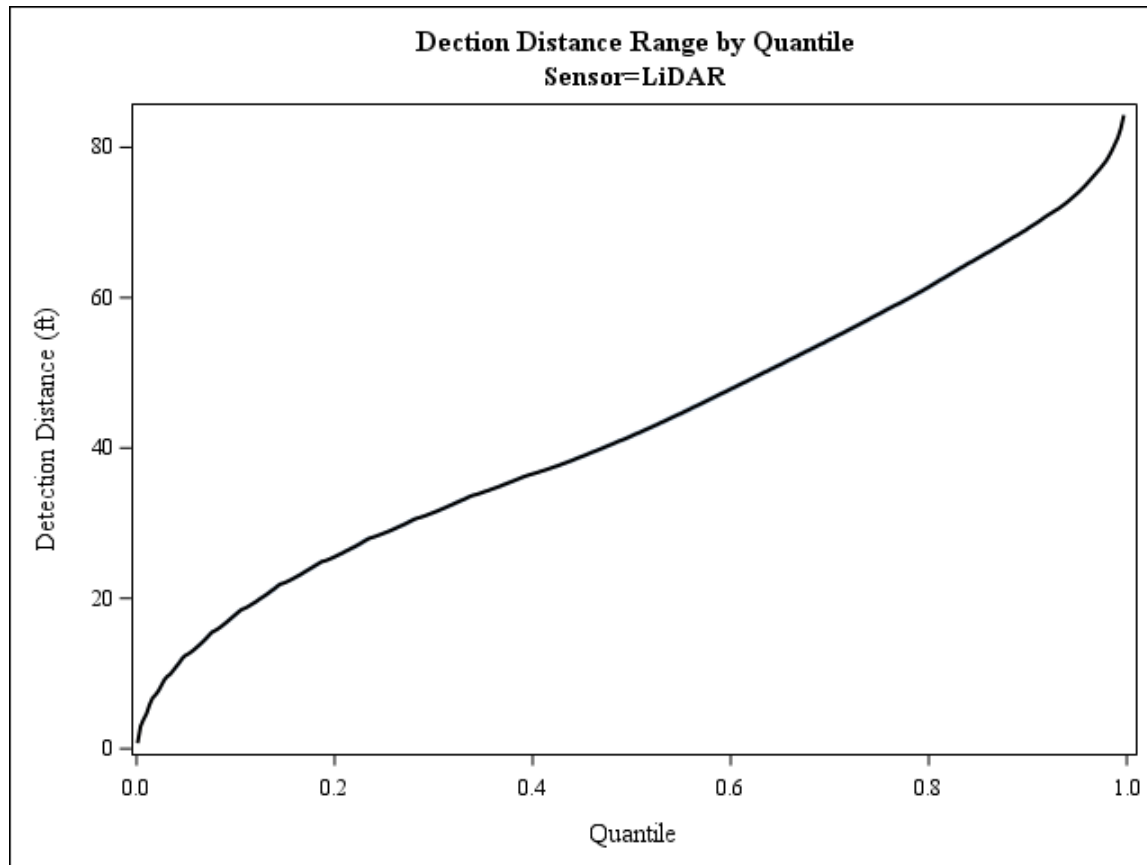


Figure 28. Graph. Detection distance by quantile for LiDAR sensor.

Thermal Range

The initial estimate for the minimum detection distance was 3.5 feet (std error = 0.11) and the initial estimate for the maximum detection distance was 125.9 feet (std error = 0.83), as shown in Table 27.

Table 27. Detection range estimates for Thermal.

Sensor	Quantile	Estimate (ft)	Std Err	95% Lower Confidence Limit	95% Upper Confidence Limit	t Value	Pr> t
Thermal	0.001	3.5	0.11	3.30	3.74	31.7	<.0001
	0.005*	6.62	0.14	6.34	6.89	47.14	<.0001
	0.990*	116.5	1.05	114.41	118.52	111.05	<.0001
	0.999	125.9	0.83	124.23	127.48	152.1	<.0001

Review of both tails showed that detections below approximately 6.6 ft and beyond approximately 116.5 ft were sparse and surrounded primarily by non-detections (Figure 29). Therefore, 6.6 ft (0.005 quantile) and 116.5 ft (0.990 quantile) were accepted as the practical minimum and maximum detection distances, respectively. The accepted detection range for Thermal was 6.6–116.5 ft.

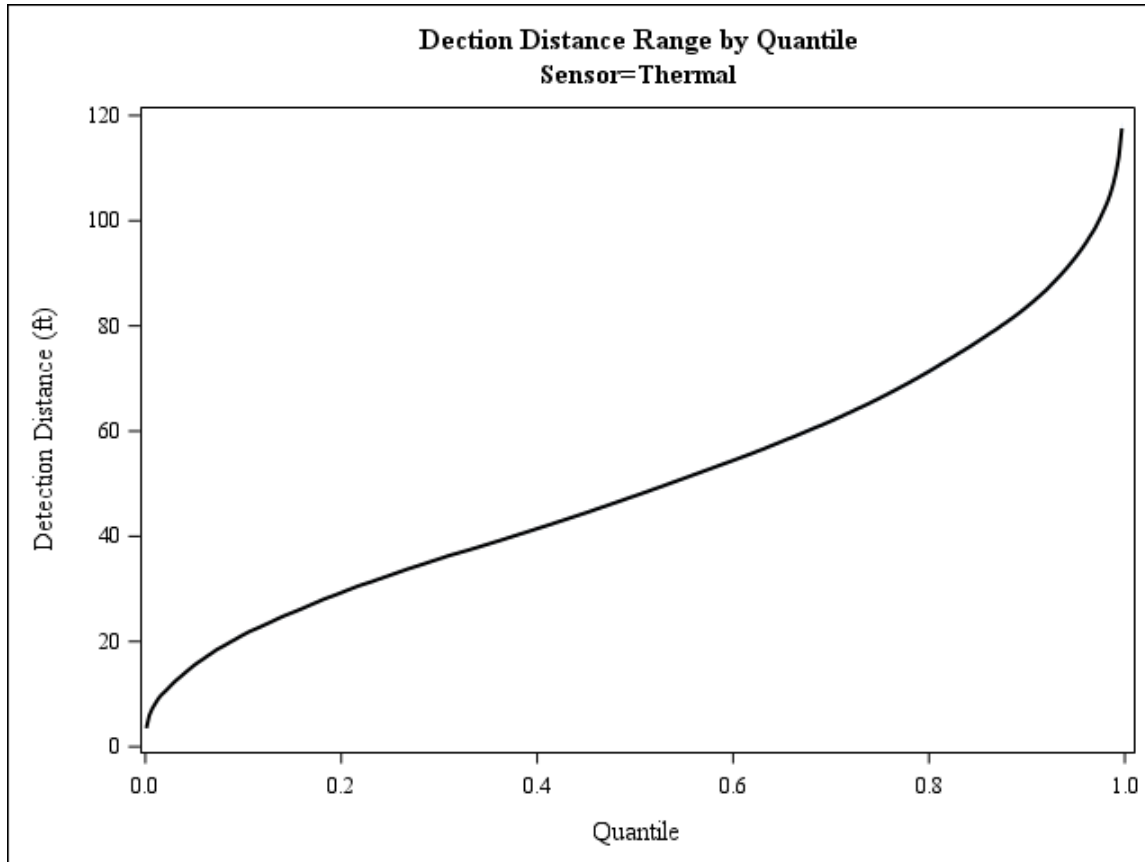


Figure 29. Graph. Detection distance by quantile for Thermal sensor

APPENDIX D

CONFIGURATION SPECIFIC DETECTION COVERAGE

PIR-1 Coverage

The PIR-1 sensor showed similar minimum distances across orientations, while maximum distance varied. The maximum detection range for 0°, 45°, 90°, and 180° orientation angles was estimated to be above 60 ft while 135°, 225°, 270°, and 315° approach angles were estimated to be under 60 ft. The resulting radial pattern was approximately circular. Modeling results for the Lumawise Cir sensor mounted at 6 meters are summarized in Table 28 and visualized in Figure 30.

Table 28. PIR-1 6m minimum and maximum bounds of detection range by height and angle.

Sensor Technology	Height (m)	Angle (°)	Min (ft)	Max (ft)
PIR-1	6	0	0.5	63.5
	6	45	0.5	66.8
	6	90	1.0	67.5
	6	135	1.0	58.1
	6	180	1.4	61.2
	6	225	1.3	58.4
	6	270	1.7	58.2
	6	315	1.9	55.7

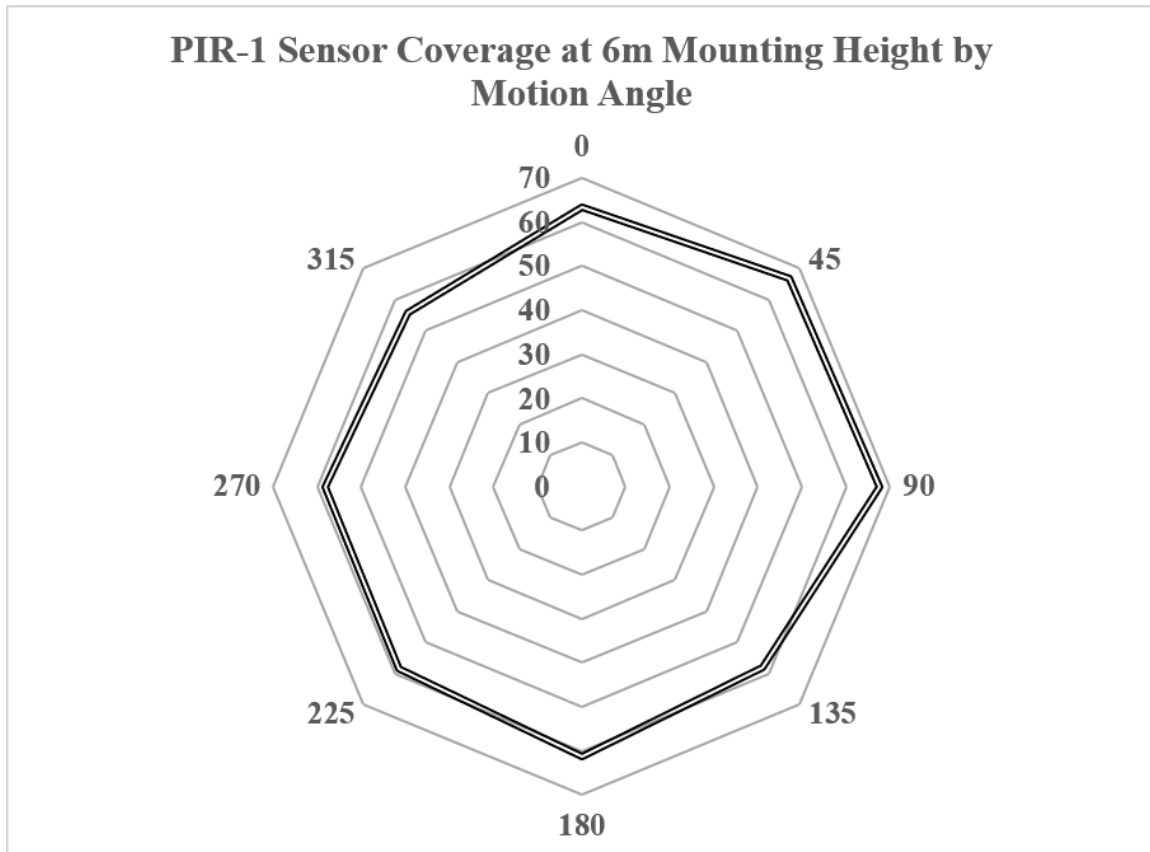


Figure 30. Coverage range by angle for PIR-1 sensor at 6m mounting height.

The PIR-1 sensor showed similar minimum and maximum distances across the 0°, 45°, and 90° orientations tested at 12 m and the results are summarized in Table 29 and visualized in Figure 31.

Table 29. PIR-1 12m minimum and maximum bounds of detection range by height and angle.

Sensor Technology	Height (m)	Angle (°)	Min (ft)	Max (ft)
Lumawise Circle	12	0	0.3	70.2
	12	45	0.4	66.9
	12	90	3.3	69.1

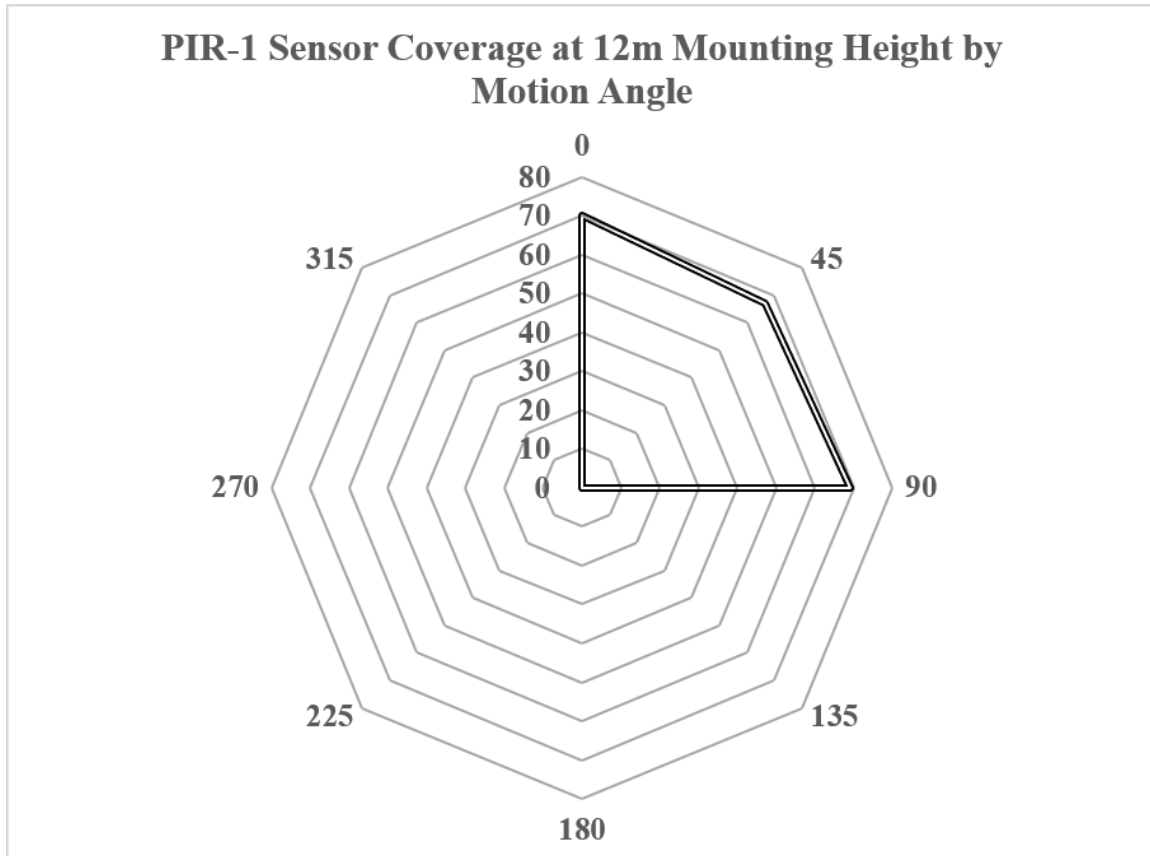


Figure 31. Coverage range by angle for PIR-1 sensor at 12m mounting height.

PIR-2 Coverage

The PIR-2 sensor showed similar minimum distances across orientations, while maximum distance varied. The maximum detection range exceeded 60 ft at 0° and 90°, while the remaining orientations were below 60 ft, with 225° having the shortest maximum range. The variation in maximum detection range produced a rectangular-like radial pattern. Modeling results for the PIR-2 sensor mounted at 6 meters are summarized in Table 30 and visualized in Figure 32.

Table 30. PIR-2 6m minimum and maximum bounds of detection range by height and angle.

Sensor Technology	Height (m)	Angle (°)	Min (ft)	Max (ft)
Lumawise Rectangle	6	0	0.4	60.2
	6	45	0.4	49.3
	6	90	0.6	62.3
	6	135	0.5	46.6
	6	180	3.1	39.7
	6	225	1.7	30.4
	6	270	2.0	46.9
	6	315	1.9	51.6

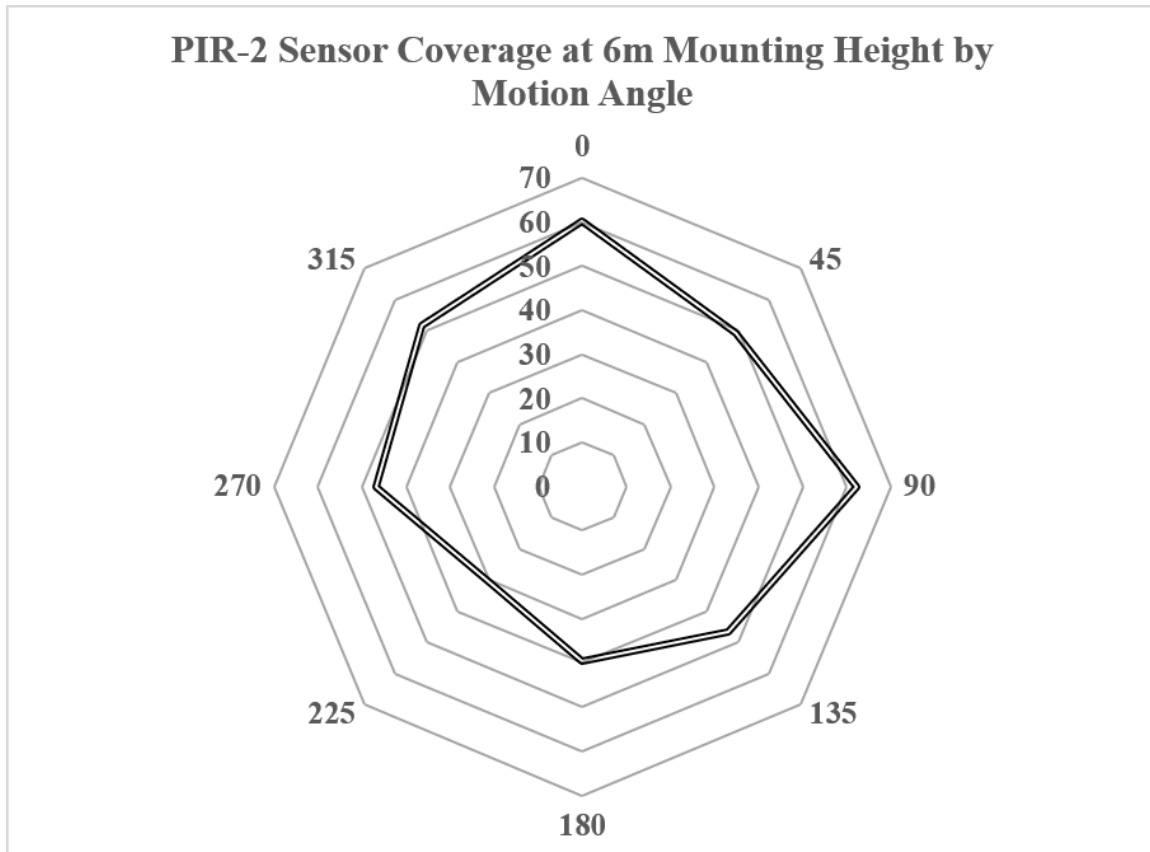


Figure 32. Coverage range by angle for Lumawise Rect sensor at 6m mounting height.

The PIR-2 sensor when mounted at 12 m, demonstrated similar minimum range at all approach angles while the 45° approach angle had a shorter estimated maximum range by 6.5-to-9.5-feet. Modeling results for the PIR-2 sensor mounted at 12 meters are summarized in Table 31 and visualized in Figure 33.

Table 31. PIR-2 12 m minimum and maximum bounds of detection range by height and angle.

Sensor Technology	Height (m)	Angle (°)	Min (ft)	Max (ft)
PIR-2	12	0	1.0	49.3
	12	45	1.3	42.8
	12	90	0.5	52.3

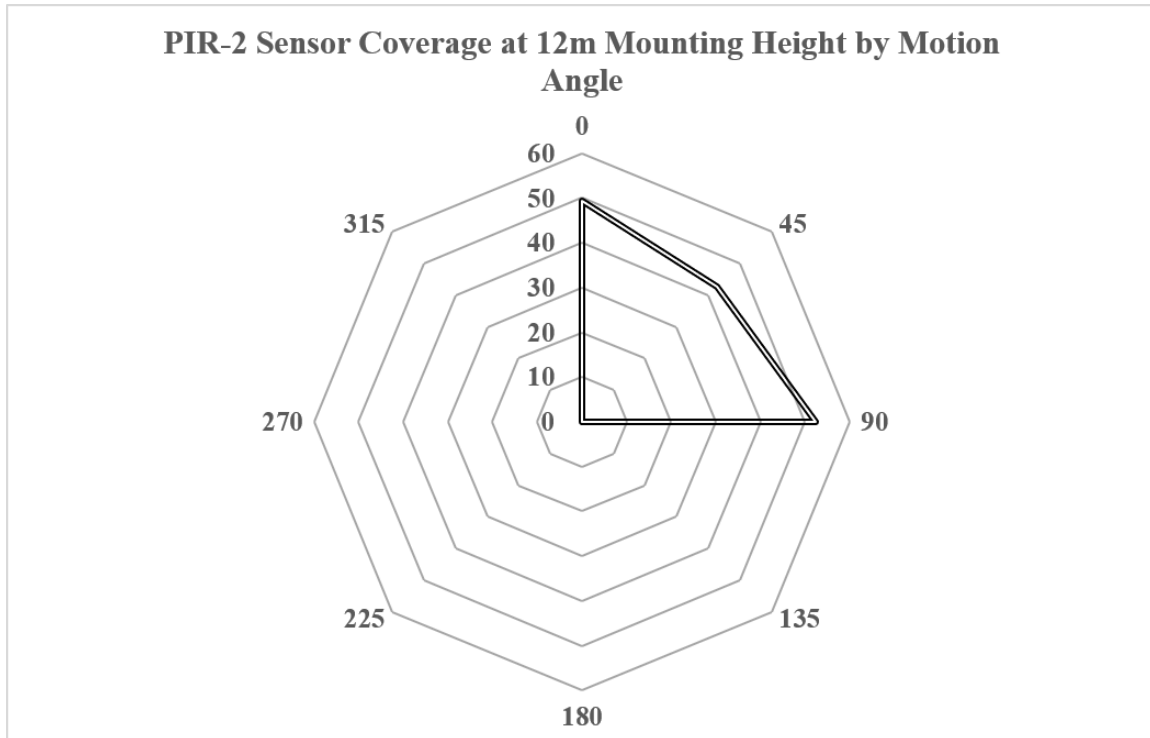


Figure 33. Coverage range by angle for PIR-2 sensor at 12m mounting height.

PIR-3 Coverage

The PIR-3 sensor showed similar minimum distances and maximum distances of 69.6–75.2 ft across the three tested orientations. At the 45° orientation angle had a shorter estimated maximum range by 3.2-to-5.6-feet. Sensor performance was consistent across approach angle. Modeling results for the PIR-3 sensor mounted at 3 meters are summarized in Table 32 and visualized in Figure 34.

Table 32. PIR-3 3m minimum and maximum bounds of detection range by height and angle.

Sensor Technology	Height (m)	Angle (°)	Min (ft)	Max (ft)
PIR-3	3	0	1.1	72.8
	3	45	1.3	69.6
	3	90	0.7	75.2

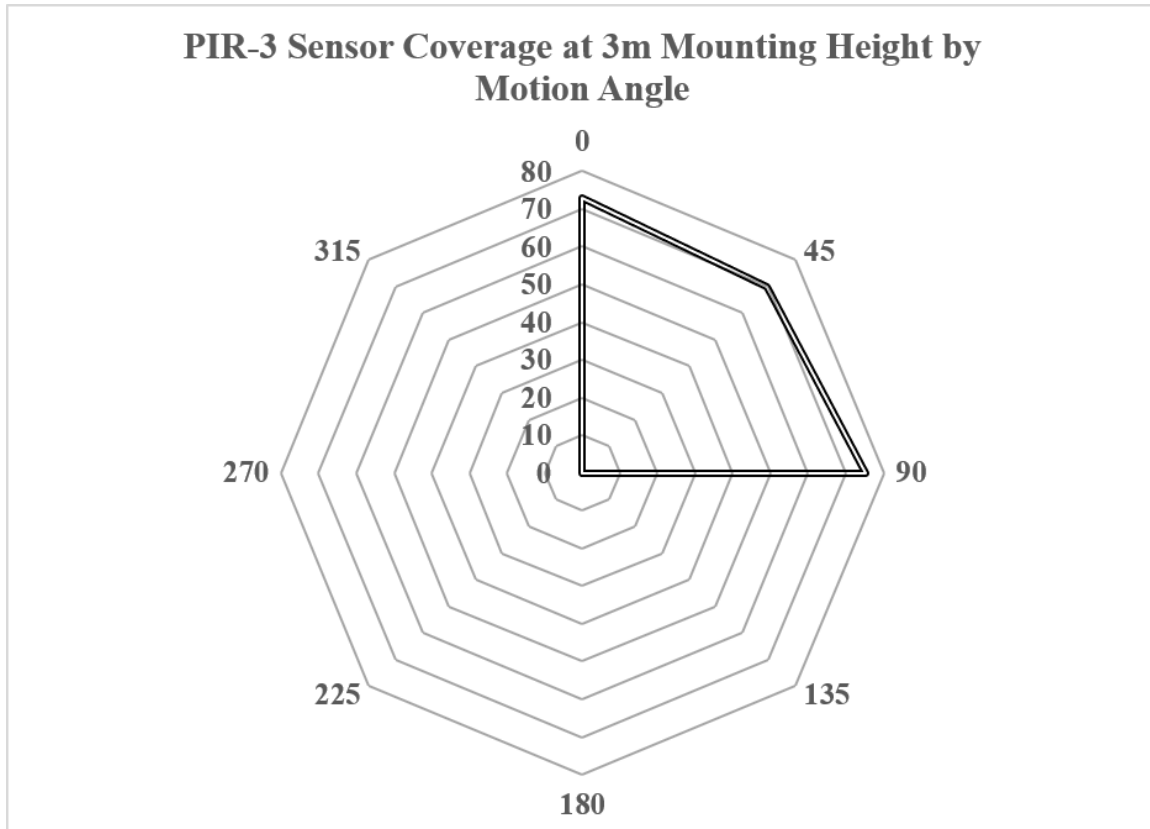


Figure 34. Coverage range by angle for PIR-3 sensor at 3m mounting height.

Hybrid-OR Coverage

The Hyb-OR sensor demonstrated similar minimum detection distances across the three tested orientations but experienced a 4.5-to-5.7-foot reduction in maximum range at 90° orientation relative to 0° and 45°. Modeling results for the Hyb-OR mounted at 3 meters are summarized in Table 33 and visualized in Figure 35.

Table 33. Hyb-OR 3m minimum and maximum bounds of detection range by height and angle.

Sensor Technology	Height (m)	Angle (°)	Min (ft)	Max (ft)
Hyb-OR	3	0	3.1	97.4
	3	45	4.8	98.6
	3	90	3.5	92.9

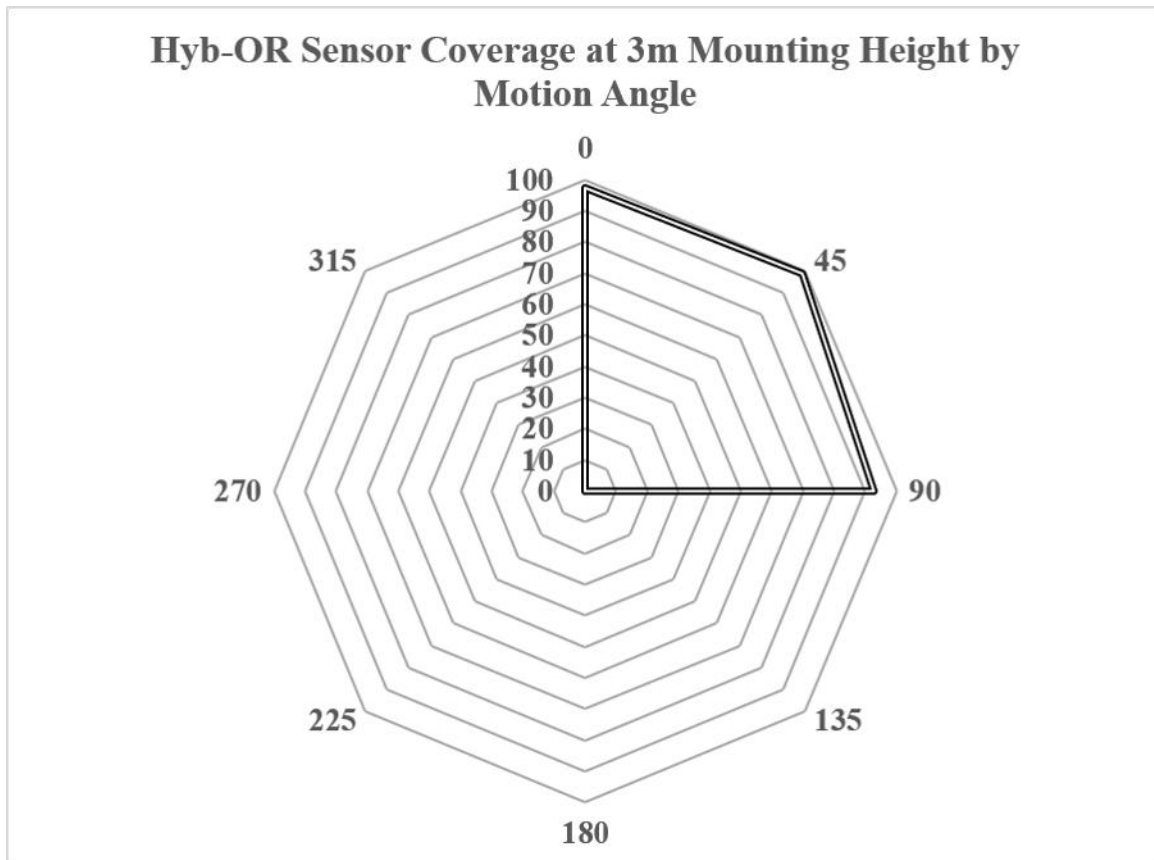


Figure 35. Coverage range by angle for Bosch PIR sensor at 3m mounting height.

Hybrid-AND Coverage

Modeling results for the Hyb-AND mounted at 3 meters are summarized in Table 34 and visualized in Figure 36. The Hyb-AND sensor showed 2.4-foot increase in minimum detection distance and a 6.8-foot decrease in maximum detection distance at 45° orientation, compared to 0°. A reliable 90° range estimate was unavailable because of data-quality limitations.

Table 34. Hyb-AND 3m minimum and maximum bounds of detection range by height and angle.

Sensor Technology	Height (m)	Angle (°)	Min (ft)	Max (ft)
Hyb-AND	3	0	6.5	71.5
	3	45	8.9	64.7

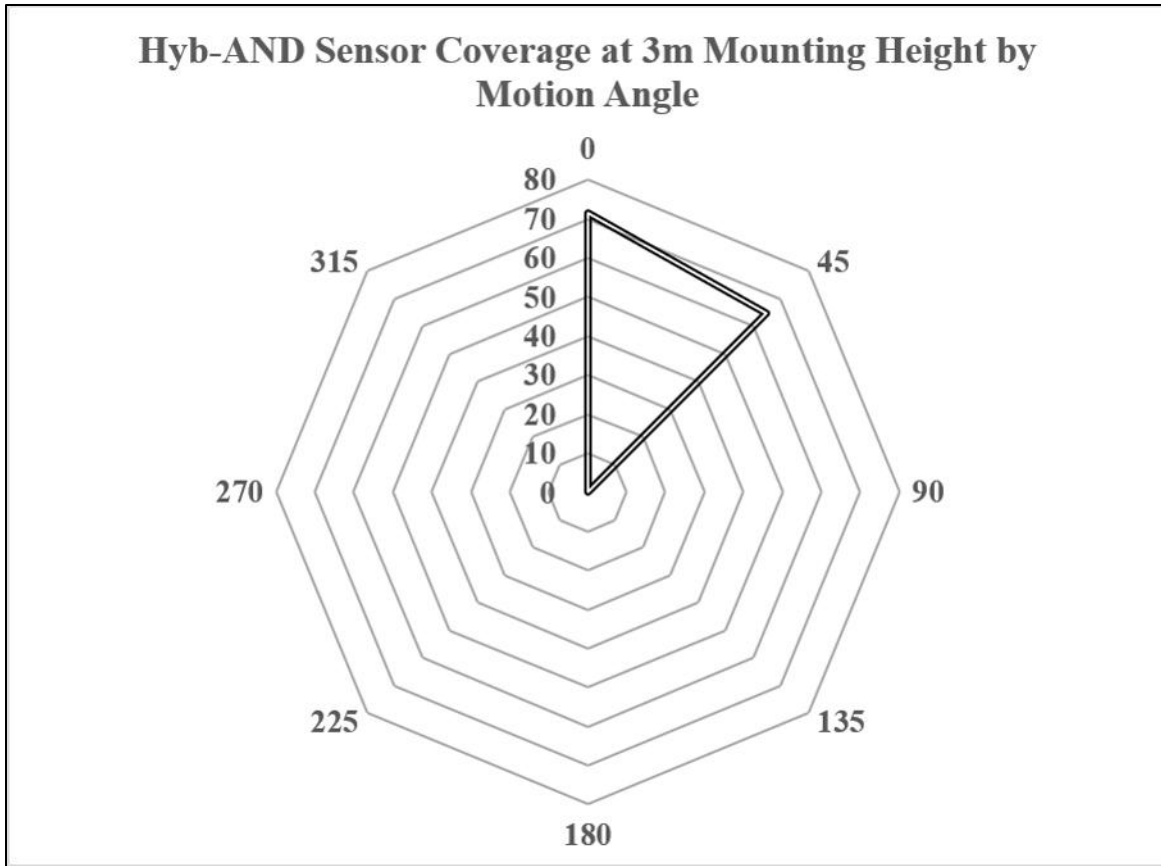


Figure 36. Coverage range by angle for Hyb-AND sensor at 3m mounting height.

LiDAR Coverage

The LiDAR sensor showed similar minimum distances and maximum distances of 80.6–84.8 ft across the three tested orientations. At the 45° orientation angle the sensor had a shorter estimated maximum range by 2.3-to-4.2-feet. Sensor performance was very consistent across approach angle. Modeling results for the LiDAR sensor mounted at 1.2 meters are summarized in Table 35 and visualized in Figure 37.

Table 35. LiDAR 1.2m minimum and maximum bounds of detection range by height and angle.

Sensor Technology	Height (m)	Angle (°)	Min (ft)	Max (ft)
LiDAR	1.2	0	0.8	84.8
	1.2	45	0.4	80.6
	1.2	90	1.1	82.9

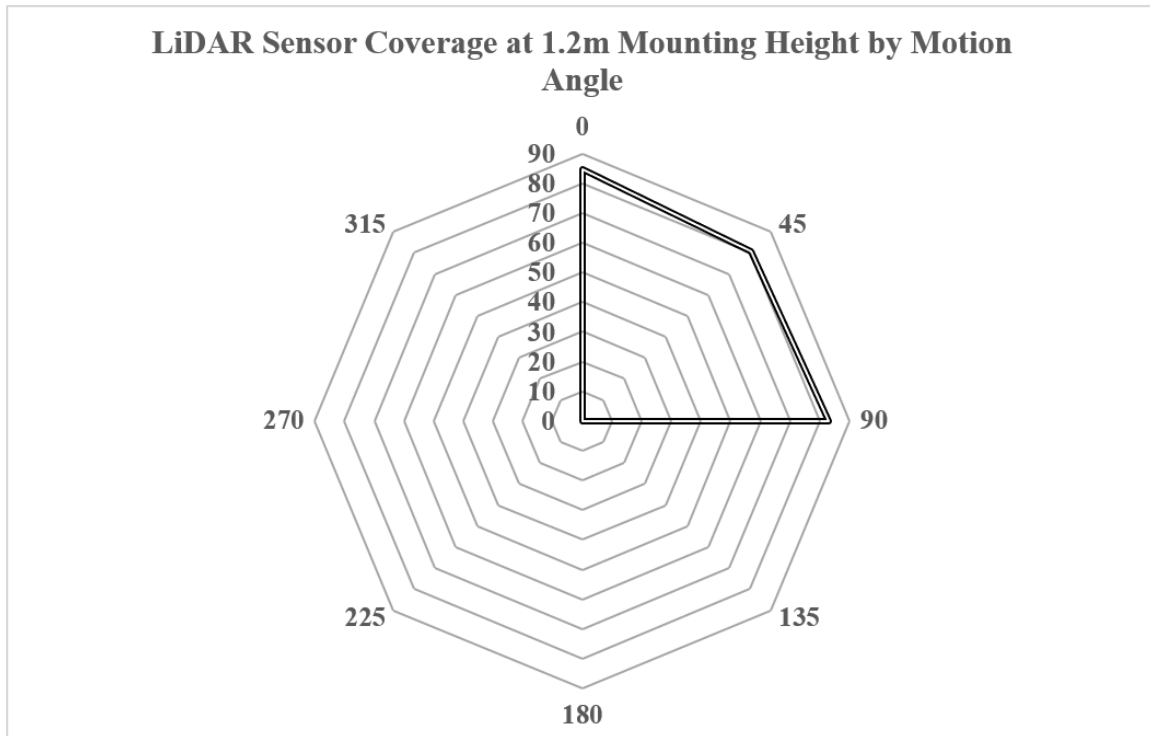


Figure 37. Coverage range by angle for LiDAR sensor at 1.2m mounting height.

Thermal Coverage

The Thermal sensor demonstrated similar minimum detection distances across the 3-m orientations, while maximum distance varied substantially. The 45° and 90° orientations produced maximum distances of 113.0 and 105.9 ft, respectively, whereas the 0° orientation produced a maximum of 61.4 ft. The Thermal sensor was also tested at 6-meter mounting height and 90° orientation which resulted in increases to the minimum (8.9 ft) and maximum (116.5 ft) detection range. Modeling results for the Thermal sensor mounted at 3 meters are summarized in Table 36 and visualized in Figure 38.

Table 36. Thermal sensor minimum and maximum bounds of detection range by height and angle.

Sensor Technology	Height (m)	Angle (°)	Min (ft)	Max (ft)
Thermal	3	0	3.7	61.4
		45	3.6	113.0
		90	2.5	105.9
	6	90	8.9	116.5

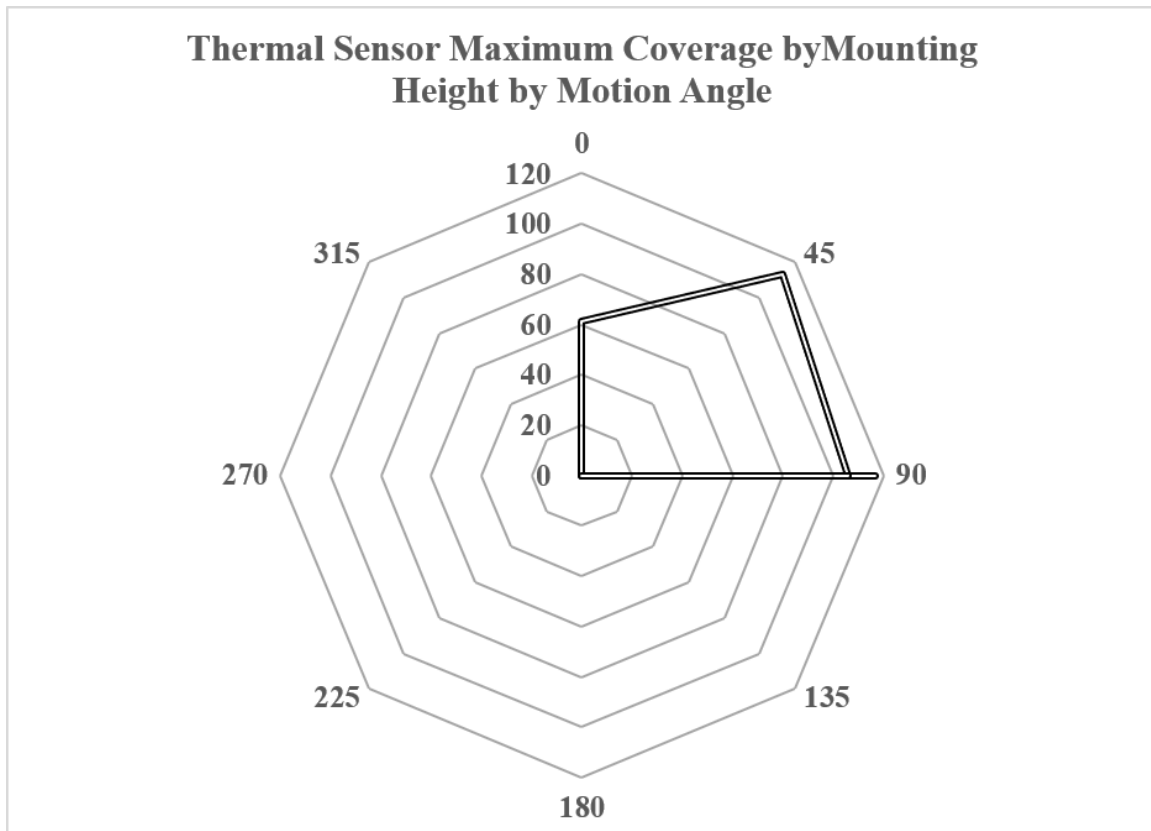


Figure 38. Coverage range by angle for Thermal sensor by mounting height.