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Smart Helmet-Based Personnel Proximity Warning System for Improving Underground Mine Safety

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Abstract: A smart helmet-based wearable personnel proximity warning system was developed to prevent collisions between equipment and pedestrians in mines. The smart helmet worn by pedestrians receives signals transmitted by Bluetooth beacons attached to heavy equipment, light vehicles, or dangerous zones, and provides visual LED warnings to the pedestrians and operators simultaneously. A performance test of the proposed system was conducted in an underground limestone mine. It was confirmed that as the transmission power of the Bluetooth beacon increased, the Bluetooth low energy (BLE) signal detection distance of the system also increased. The average BLE signal detection distance was at least 10 m, regardless of the facing angle between the smart helmet and Bluetooth beacon. The subjective workload for the smartphone-, smart glasses-, and smart helmet-based proximity warning system (PWS) was evaluated using the National Aeronautics and Space Administration task load index. All six workload parameters were the lowest when using the smart helmet-based PWS. The smart helmet-based PWS can provide visual proximity warning alerts to both the equipment operator and the pedestrian, and it can be expanded to provide worker health monitoring and hazard awareness functions by adding sensors to the Arduino board.

Keywords: mine safety; smart helmet; personnel proximity warning system; Bluetooth beacon; Arduino

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1. Introduction

In underground mines, worker safety accidents frequently occur, owing to collisions between equipment and pedestrians or other equipment. The U.S. Bureau of Labor Statistics stated that there were 45 fatalities due to equipment collisions in underground mines in the United States between 2011 and 2019 [1]. Accidents were mainly caused by being caught in running machinery, struck by powered vehicles, or compressed by equipment. According to a disaster report published by the government of Western Australia, there have been a total of 34 equipment collisions involving haulage trucks and charge-up trucks in underground mines in Western Australia since 2015 [2].

Proximity warning systems (PWSs) have been developed to prevent equipment collision accidents in underground mines. PWSs provide visual and/or audible proximity alerts to equipment operators of pedestrians or other equipment approaching within a certain distance [3]. The National Institute for Occupational Safety and Health (NIOSH) in the U.S. has developed PWSs using radio-frequency identification (RFID) and electromagnetic signals. Ruff and Hession-Kunz [4] developed an RFID-based collision warning system to provide a proximity warning to equipment operators when a pedestrian approaches a front-end loader. Active tags were attached to the belt or cap of a pedestrian worker, and an RFID reader was installed on the front-end loader to recognize the unique ID of the active tag. This system sets the progressive sensing distance (near, middle, and far) and provides visual and audible alerts to the equipment operator through lamps and buzzers. Schiffbauer [5] suggested the hazardous area signaling and ranging device to provide a proximity warning to the equipment operator approaching a continuous miner. The wire loop antenna was installed on a continuous miner to generate a magnetic field. The receiver measured the magnetic field strength and provided visual, audible, and vibration alerts to the equipment operator when the magnetic field strength exceeded a certain threshold. Various commercial products based on PWSs developed by the NIOSH have been released [6–10].

Bluetooth low energy (BLE) technology has been actively applied in the development of PWSs in underground mines. BLE is a Bluetooth 4.0 communication technology in the 2.4 GHz band that was launched in 2010 [11]. Compared to the existing Bluetooth classic technology, this enables high-speed data transmission with low power consumption [12]. Baek and Choi [13] proposed a Bluetooth beacon-based PWS that provides proximity alerts to equipment operators using a smartphone. A Bluetooth beacon was attached to the pedestrian worker's helmet, haulage equipment, and dangerous areas. In addition, a smartphone was mounted on the equipment. The smartphone measured the received signal strength indicator (RSSI) of the BLE signal and provided visual, audible, and vibration alerts when the RSSI exceeded a certain threshold. Park and Choi [14] implemented a system in an underground limestone mine and successfully demonstrated the system utility. However, existing PWSs provide only one-way proximity warnings to equipment operators through in-cab screens, such as smartphones and tablets installed inside the equipment. Consequently, it is difficult for pedestrian workers to be aware of the collision risks in underground mines.

Various wearable PWSs have been proposed to provide proximity warnings to pedestrian workers. In contrast to conventional PWSs, signal transmitters were installed on the equipment, and receivers were attached to pedestrian workers. Wearable PWSs can be classified into worn-type personal alarm devices (PADs), smart vests, and smart glasses. PADs can be worn on the worker's belt, pocket, and cap, and mainly provide audible or vibrating alerts. Examples of commercialized PAD products are ELOsheld by ELOCKON [15], Smartzone proximity system by Komatsu & JoyGlobal [16,17], HazardAvert® by STRATA [18], and more [19–22]. Smart vests provide vibration alerts using haptic or tactile sensors [23,24]. Recently, a smart glass-based PWS was developed using BLE technology [25]. Bluetooth beacons were installed on the equipment, and the pedestrian worker wore smart glasses. Smart glasses measured the RSSI of the BLE signal and provided a proximity warning when the RSSI was above a certain threshold. However, existing wearable PWSs provide one-way proximity warnings to pedestrian workers only. Therefore, it is necessary to develop new PWSs that can provide proximity warnings in both directions, to the equipment operator and the pedestrian worker simultaneously.

Recently, smart helmet technology has been widely used by bicycle and motorcycle users [26]. A smart helmet is a technology that monitors a user's health, surrounding environment, and equipment status. In addition, it collects real-time data using wireless sensors and communication technologies. The main functions of the smart helmet include hazard–risk recognition, vehicle condition monitoring, and convenience. The smart helmet immediately determines the user's health condition [27], requests rescue [28], and provides a risk alert [29]. In addition, it provides motorcycle speed and fuel level information to the user in real-time [30] and has convenient functions such as navigation, music playing, and device connection [31]. Efforts are being made to increase workplace safety and convenience by applying smart helmet technology to various fields, such as construction [32], manufacturing [33], and petrochemical work [34]. In the mining industry, many research cases have been presented to implement worker health monitoring, hazard awareness, and wireless communication [35–44]. However, a smart helmet-based PWS using BLE technology has not yet been developed to provide bidirectional proximity warnings to equipment operators and pedestrian workers in underground mines.

The purpose of this study is to develop a smart helmet-based PWS that can provide simultaneous proximity warnings to both equipment operators and pedestrians in underground mines. Bluetooth beacons are installed on mining equipment such as dump trucks, excavators, and loaders, and pedestrian workers wear the smart helmet-based PWS. When the equipment approaches the pedestrian worker, the smart helmet recognizes the BLE signal and emits an LED light. This study analyzed the BLE signal detection distance of the smart helmet for two conditions in the underground mine. One was the Tx power condition of the Bluetooth beacon and another was the facing angle condition between the smart helmet and the Bluetooth beacon. The NASA task load index (NASA-TLX) [45] was analyzed to evaluate the subjective workload felt by the equipment driver and the pedestrian worker for PWSs based on smartphones, smart glasses, and smart helmets.

2. Design of the Proximity Warning System (PWS) Based on Bluetooth Beacons and Smart Helmets

The design of PWS based on Bluetooth beacons and smart helmets is summarized in Figure 1. The smart helmet worn by the worker receives a BLE signal transmitted from the Bluetooth beacon and provides a visual alert when it comes close to the beacon. The Bluetooth beacon can be attached to heavy equipment, a management vehicle, or a dangerous area at the mine site, and the attached beacon continuously transmits the BLE signal. The smart helmet can warn wearers of access to heavy equipment or vehicles and access dangerous areas and warn drivers that there are workers nearby. Visual proximity alerts are received through a smart helmet while working on the spot; therefore, both workers and drivers can quickly detect and respond to dangerous situations.

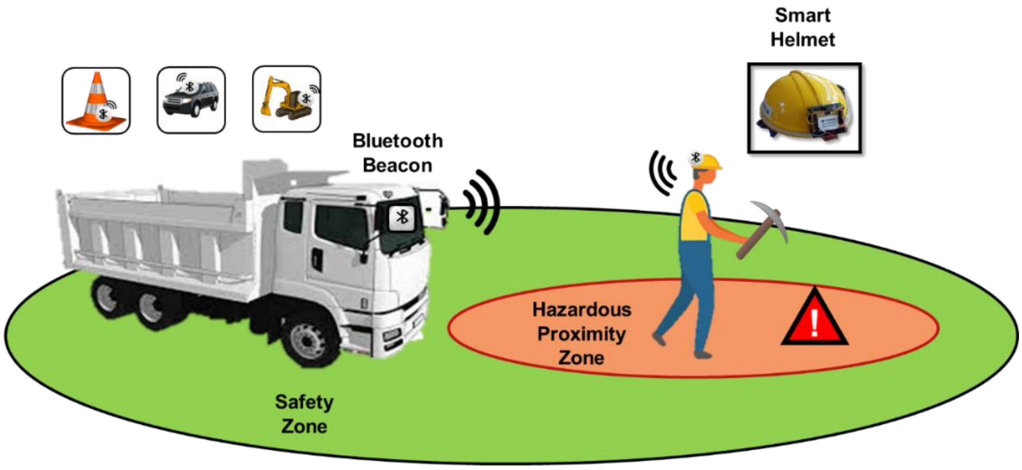


Figure 1. Overview of personal proximity warning system (PWS) using smart helmet.

2.1. Design of BLE Transmission Units Using Bluetooth Beacon

Bluetooth beacons periodically transmit information, including the general-purpose unique identifier of the beacon and media access control (MAC) address through the BLE signal. The intensity of the BLE signal transmitted by the Bluetooth beacon is expressed as Tx power, and the unit is dBm. The received intensity of the BLE signal can be quantified using the RSSI value. RSSI is represented in a negative form by a value between −99 dBm and −35 dBm. The propagation distance of the BLE signal may vary depending on the signal transmission intensity and direction of the signal propagation of the Bluetooth beacon. An increase in the BLE signal transmission intensity increases the signal propagation distance. The signal propagation direction is bidirectional, and the signal can be spread uniformly in all directions, but this limits the propagation distance. The BLE signal is first propagated relative to the Bluetooth beacon when the signal is transmitted as the directional signal. The change in RSSI according to the BLE signal transmission intensity and the direction of the radio wave of the Bluetooth beacon was previously analyzed [46].

Bluetooth beacons can communicate with peripheral devices in three ways: point-to-point, broadcast, and mesh. The point-to-point method is a method of exchanging data by pairing the master device transmitting a large amount of data and the slave device receiving data at 1:1. The broadcast method is a method in which the observer receives information when the broadcast periodically transmits its ID information to the peripheral devices. Bluetooth beacons are mainly broadcast missions, and observers mainly use PCs and smartphones. The mesh method is connected to several master and slave devices [46].

In this study, RECO beacons (Perples, Seoul, Korea) were used as BLE transmission devices. RECO beacons are certified by institutions in Korea, the United States, Europe, and Japan and meet global beacon standards (Table 1). Figure 2 shows examples of heavy equipment and vehicles at the mine site with RECO beacons. A Bluetooth beacon was installed on the back of the room mirror on the front of the truck, and a Bluetooth beacon was provided on the front of the heavy equipment. The Bluetooth beacons set the directional signal such that the signal could be propagated further. The signal transmission strength and period of the beacons were set to −4 dBm and 1 s, respectively.

Table 1. Specifications of the RECO beacon [47].

Item		Value
Dimensions (Diameter × Height)		45 mm × 20 mm
Weight		11.6 g (0.4 oz)
Processor		32-bit ARM® Cortex®-M0
Battery		CR2450 Lithium Coin Battery (3 V, 620 mAh)
Casing		Acrylonitrile Butadiene Styrene (ABS) Plastic
Chipset		Nordic nrf51822
Thermal Resistance		93 °C (200 °F)
Operating Temperature		−10–60 °C (14–140 °F)
Wireless Technology		Bluetooth 4.0 (i.e., BLE or Bluetooth® Smart)
Signal range		1 m~70 m (3.2 ft~230 ft)
Signal transmission period		Min (10 ms), Max (2 s)
Transmission power		Min (−16 dBm), Max (4 dBm)
Certification	South Korea	Korea Certification (KC)
	USA	Federal Communication Commission (FCC)
	Europe	Conformité Européene (CE) marking
	Japan	Ministry of Internal Affairs and Communications (MIC) of Japan

(a) (b) (c) (d)

Figure 2. Bluetooth beacons attached to trucks (**a**,**b**) and excavators (**c**,**d**).

2.2. Design of BLE Receiver Units Using an Arduino Board

Arduino is an open source electronic platform based on easy-to-use hardware and software (Table 2). The Arduino board reads the input data, including sensor illumination and button pressing and converts it into output data. Because the Arduino board and software are open sources, users can independently build boards to adjust the system to meet specific needs [48].

Table 2. Specifications of the Arduino Uno board [49].

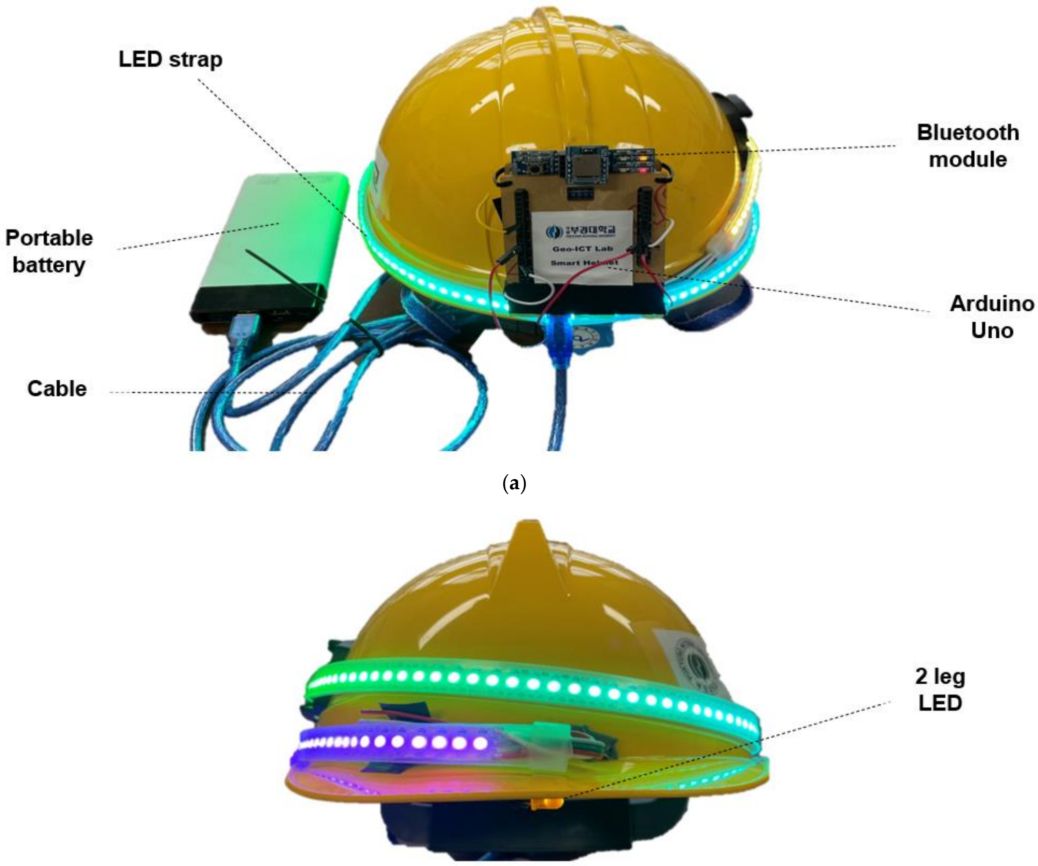
Item	Value
Model	Arduino Uno R3
Microcontroller	ATmega328P
Length	68.6 mm
Width	53.4 mm
Weight	25 g
Operating Voltage	5 V
Input Voltage	7–12 V (recommended), 6–20 V (limit)
Digital I/O Pins	14 (of which 6 provide PWM output)
PWM Digital I/O Pins	6
Analog Input Pins	6
DC Current per I/O Pin	20 mA
DC Current for 3.3V Pin	50 mA
Flash Memory	32 KB (ATmega328P) of which 0.5 KB used by bootloader
SRAM	2 KB (ATmega328P)
EEPROM	1 KB (ATmega328P)
Clock Speed	16 MHz
LED_BUILTIN	13

In this study, a smart helmet was developed to develop a wearable personal PWS for workers. The smart helmet was made by combining an Arduino Uno board, Bluetooth BLE module (FBL780BC, Table 3), LED strap, and two-leg LEDs with the safety helmet worn by mining workers. Figure 3a,b show the exterior shape of the equipment divided into front and rear parts. The smart helmet provides visual warnings through LED straps (using two-leg LEDs), and receiving power through portable batteries. The Bluetooth BLE module (FBL780BC) supports Bluetooth Low Energy, a low-power function based on Bluetooth 4.1.

Table 3. Specifications of Bluetooth module [50].

Item	Value
Model	FBL780BC
Bluetooth specification	Bluetooth4.1Low Energy Support
Communication distance	10 m
Frequency range	2402~2480 MHz ISM Band
Sensitivity	−94 dBm
Transmit power	2 dBm (−3 dBm: Actual value after matching)
Size	15.5 mm × 18.5 mm
Input power	3.3 V
Current consumption	Peripheral: 3 mA (Max), Central: 21 mA (Max: Scanning)
Operating temperature	Min: −10 °C, Max: 50 °C
Communication speed	2400 bps~230,400 bps
Antenna	Chip Antenna
Interface	UART

The circuit diagram was used to visualize the connection method of the Arduino board, LED, and Bluetooth module as shown in Figure 4. The process of the operating algorithm of the smart-helmet PWS is illustrated in Figure 5. After the BLE signal was received via the Bluetooth BLE module attached to the smart helmet, it was compared to the MAC address of the Bluetooth beacon stored in the database. If the MAC addresses of the Bluetooth beacons are matched, the LED strap and two leg LEDs are turned on for 30 s to provide a visual alert to the worker and the driver and, if not, they are not turned on. The system is designed to operate repeatedly through infinite loops when power to the Arduino board is turned on.



(**a**)

(**b**)

Figure 3. The component of the smart helmet. The rear part (**a**) and the front part (**b**) of the helmet.

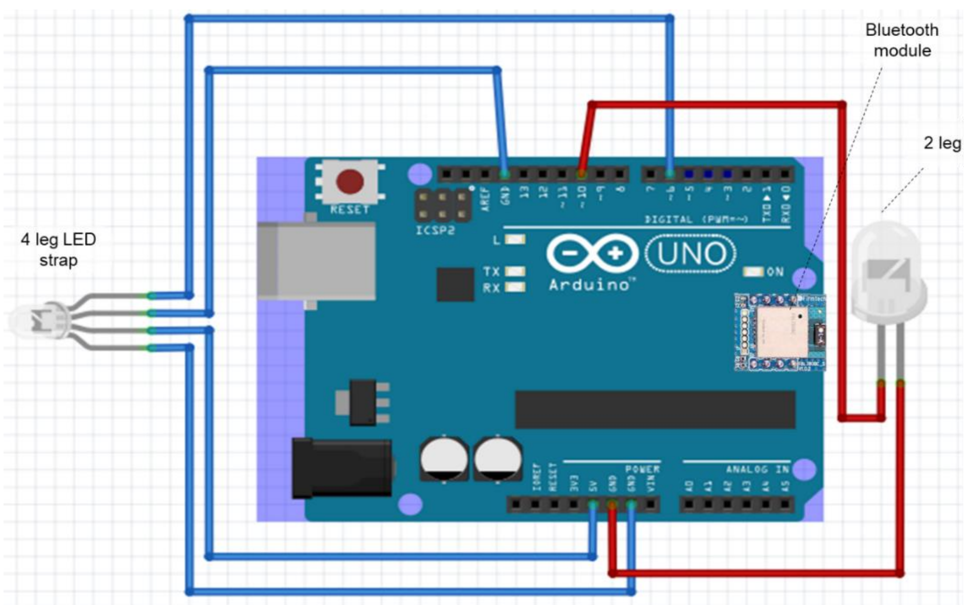


Figure 4. Circuit diagram of Arduino application.

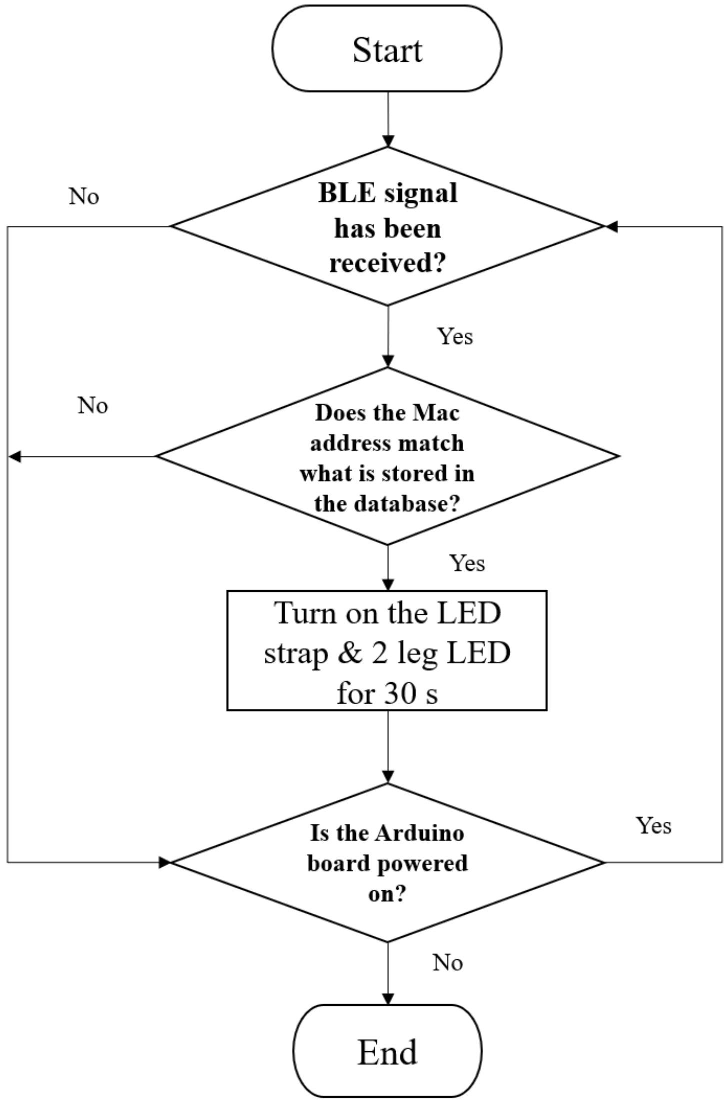


Figure 5. The process of the operating algorithm for the smart helmet-based personal proximity warning system.

3. Experiment of the Proximity Warning System Based on Bluetooth Beacon and Smart Helmet

3.1. Performance Evaluation of Personal PWS Based on Smart Helmets

To evaluate the performance of the developed smart helmet-based personal PWS, a field experiment was conducted at the Sungshin Minefield underground limestone mine (37°17′12″ N, 128°43′53″ E) located in Jeongseon-gun, Gangwon-do, Korea. Figure 6 shows the tunnels that have been tested in the field on a two-dimensional and three-dimensional map and an actual photograph. As shown in Figure 2, a Bluetooth beacon was attached to the back of the room mirror in front of the truck and the front of the heavy equipment, and the workers wore a smart helmet programmed with a personal PWS system. A Bluetooth module capable of receiving BLE signals is placed at the back of the helmet to recognize the proximity of equipment outside the worker's view. A field experiment was conducted to measure the detection distance of the BLE signal received by the smart helmet by adjusting the Tx power of the Bluetooth beacon. The angle between the Bluetooth beacon and the smart helmet was adjusted to measure the detection distance of the smart helmet receiving the BLE signal.

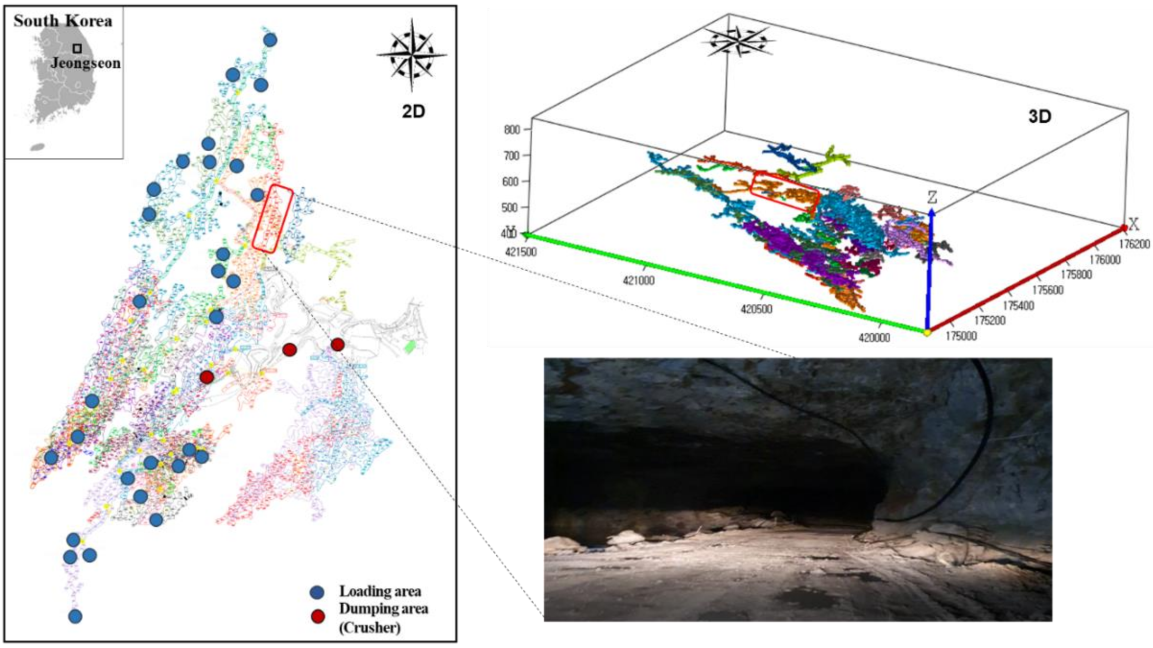
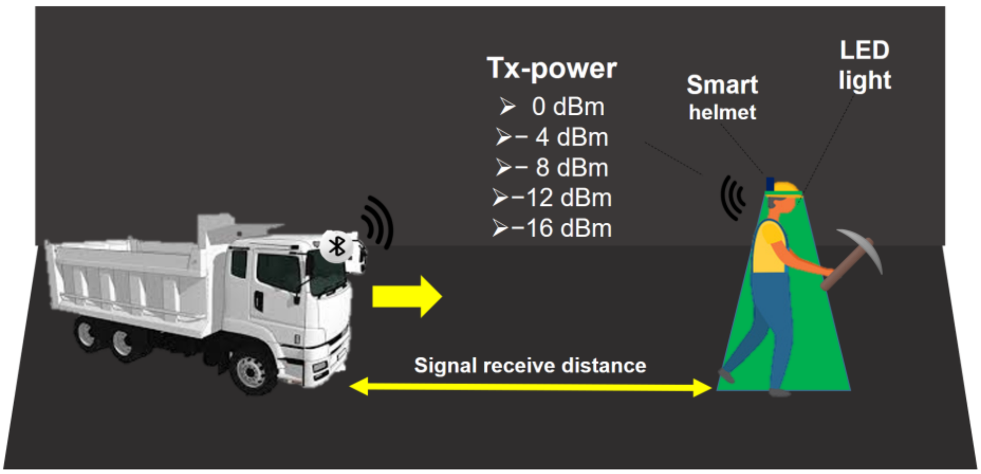


Figure 6. Underground map of the study area (Sungshin Minefield underground limestone mine, Jeongsun-gun, Gangwon-do, Korea) in 2- and 3-dimensions, and an actual photograph.

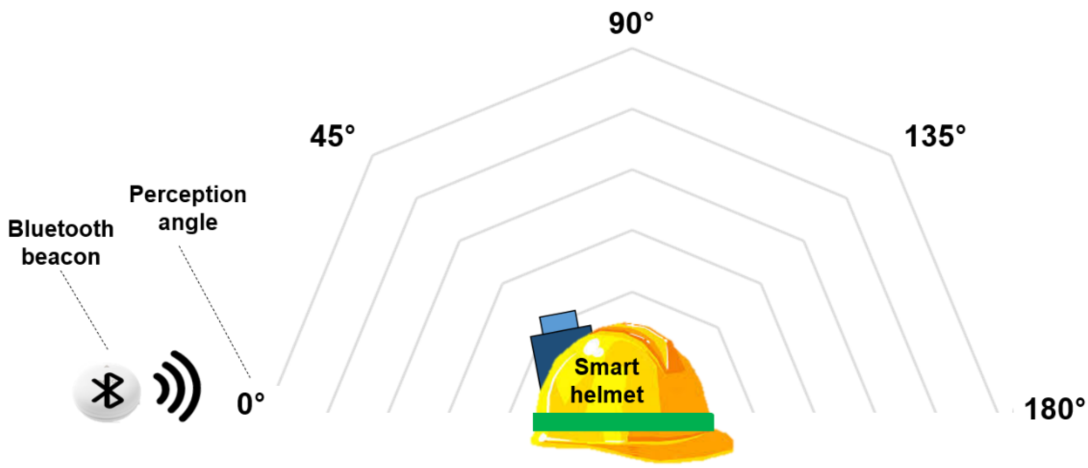
Figure 7a shows the smart helmet measuring the detection distance of receiving the BLE signal for each Tx power. The Bluetooth module that receives the BLE signal was installed at the rear of the helmet, and the Bluetooth module and Bluetooth beacon attached to the vehicle were arranged to face each other. The Bluetooth beacon, attached to the truck, approached a pedestrian standing on a mineway transport route 100 m away at a speed of 10–20 km/h. We then measured the detection distance at which the personal PWS receiving the BLE signal began warning pedestrians. The Tx power was set at 4 dBm intervals—from −12 dBm to 4 dBm—and measured 10 times for each Tx rower (50 times total).

Figure 7b shows an experiment that measures the detection distance of a smart helmet receiving a BLE signal via adjusting the angle between the Bluetooth beacon and the smart helmet. Similar to the above experiment, the truck approached at speeds of 10–20 km/h, and the detection distance at which the warning commenced was measured. The angles between the smart helmets and beacons were set at 45° intervals—from 0° to 180°, and measured 10 times for each angle (50 measurements in total).



(**a**)

Figure 7. *Cont.*



(**b**)

Figure 7. Overview of the performance test of the smart-helmet based PWS. (**a**) Experimental model of BLE signal detection distance measurement performed by considering the Tx power of the Bluetooth beacon; (**b**) BLE Signal detection distance measurement model according to the perception angle between the Bluetooth beacon and the smart helmet.

3.2. Subjective Workload Assessment of Smart Helmet-Based Personal PWS

Workload is a quantitative measure of the amount of mental stress a person experiences while performing tasks within a particular system [51]. Workload is affected by psychological (focus on work and anxiety), physical (physical difficulties and difficulty in controlling machines), temporal (deadlines), and environmental (noise and relationships with colleagues) factors [52]. If the workload is not properly adjusted when designing the system, overload can occur, and the work efficiency can be reduced. Therefore, it is necessary to improve the work efficiency by designing and operating a system with minimal workload.

Subjective workload evaluation can be performed using a questionnaire. It is frequently used in human–machine system development [53]. Representative subjective workload evaluation methods include the NASA-TLX [45], subjective workload assessment techniques [54], and workload profile techniques [55]. In this study, subjective workload was evaluated using the NASA-TLX method. The psychological, physical, and temporal effects on workers using the personal PWS while wearing smart helmets and working at the mining site were evaluated. The NASA-TLX is a multidimensional grading procedure that estimates the overall workload score based on a weighted average of six factors [56]: mental, physical, temporal, overall performance, effort, and frustration. These workload parameters are defined as follows:

- Mental demand: how many mental and cognitive skills are needed to accomplish this task?
- Physical demand: how much physical ability do you need to perform this task?
- Temporal demand: how much duress did you feel due to the rate or pace at which you performed multiple tasks?
- Overall Performance: how successfully do you think you have achieved the goals of this task?
- Effort: how much mental and physical effort was required to achieve your work goals?
- Frustration Level: how much discomfort have you felt while working on this task?

The response of the worker to these the six workload parameters was evaluated. All the parameters except for "Overall Performance" (scoring from good to bad) were graded from low to high with values between 0 and 100 (in increments of 5). The weights of the six parameters were calculated using pairwise comparisons, and the overall workload score was calculated by averaging the product of each factors score and weight.

Figure 8 is a schematic showing the experiment conducted. Three equivalent experiments were performed under the same experimental conditions to compare the effect on the subjective workload. In this study, the subjective workload evaluation was performed on 10 experimental subjects aged 24 to 26 years old (average age was 24.9 years) at the same location where individual PWS performance was evaluated. More than half (60%) of the test subjects said they had knowledge of smart glasses, and the majority (80%) said they had no knowledge of smart helmets. The test subjects used (a) a smartphone-based personal PWS (driver's position), (b) a smart glass-based personal PWS (worker's position), and (c) a smart helmet-based personal PWS (worker and driver's position). For this experiment, we used the smartphone-based personal PWS by Baek and Choi [13], the smart glass-based personal PWS by Baek and Choi [25] and the smart helmet-based personal PWS developed in this study.

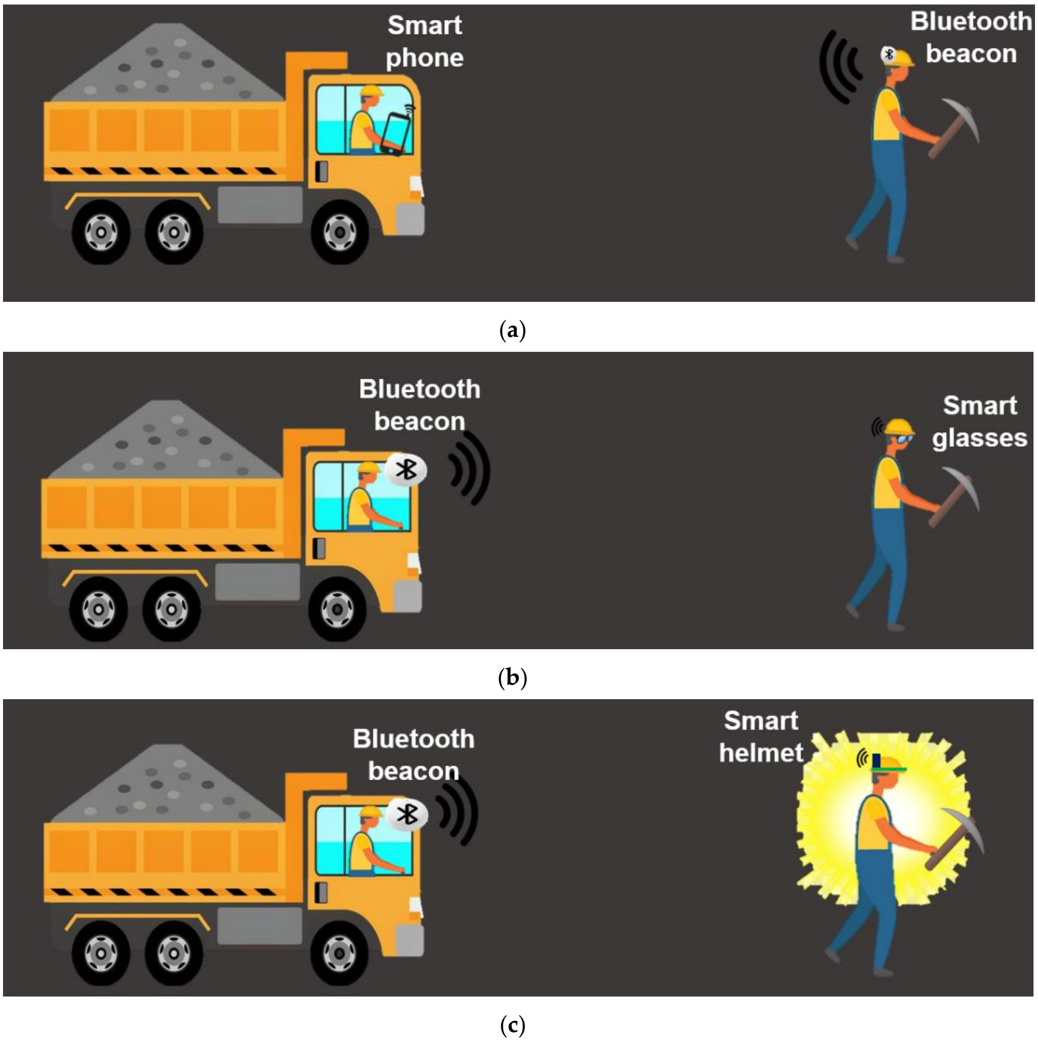


Figure 8. Overview of the subjective workload assessment. (**a**) Type 1: truck drivers wearing the smartphone-based PWS; (**b**) type 2: pedestrian workers wearing the smart glasses-based PWS; (**c**) type 3: truck drivers and pedestrian workers wearing the smart helmet-based PWS.

In the experiments, the test subject stood at the center of the transport route and examined the condition of the transport route (worker's position) or boarded a truck or loader (driver's position) to approach the subject. The smartphone provided a proximity warning to the driver with a hazard warning image. Smart glass provides a proximity alert to a worker with a hazard warning image. The smart helmet turned on the LED to provide a visual warning to both the driver and worker. In one case, the test subject boarded a loader or truck (driver's position) and when the device sensed that the worker was nearby, the vehicle was stopped temporarily. The worker passed only after confirming the evacuation. In another case, the test subject examined the transport route's maintenance status (worker's position), and the operation was stopped when the device sensed that a vehicle was approaching. The subject evacuated to the side of the transport route, and only after the vehicle had passed did the operation resume.

Each of the 10 test subjects performed experiments (a) to (c) in random order, and after the experiment, the workload was examined according to the NASA-TLX procedure.

4. Results

Figure 9a shows the worker wearing a smart helmet when a BLE signal is not received, and Figure 9b shows the worker wearing a smart helmet when a BLE signal is received. The MAC address of the Bluetooth beacons to be attached to the mining equipment was stored in a personal PWS application program, and the smart helmet PWS was designed to provide visual alerts through LEDs when the BLE signals were received. Through the visual alarm, through LEDs, both the worker and driver can recognize the danger in advance and prevent accidents.

(**a**) (**b**)

Figure 9. Experimental results showing the performance of the smart-helmet based PWS. (**a**) Worker wearing the smart helmet when no BLE signal is received; (**b**) worker wearing the smart helmet when a BLE signal is received.

Table 4 shows the statistics of the detection distance measurement when a proximity alarm was provided according to the change in the Tx power of the Bluetooth beacon, and Figure 10 shows the average detection distance per Tx power as a graph. The average detection distance is 2.9 m at −12 dBm, 6.0 m at −8 dBm, 27.1 m at −4 dBm, 62.7 m at 0 dBm, and 66.9m at 4 dBm. As the Tx power increased, the smart helmet's BLE signal detection distance also increased.

Table 4. Statistical analysis results of BLE signal detection distance (m) of the smart helmet according to the Tx power of Bluetooth beacon.

BLE Signal Recognition Distance (m)	Signal Transmission Strength of Bluetooth Beacon				
	−12 dBm	−8 dBm	−4 dBm	0 dBm	4 dBm
Mean	2.9	6.0	27.1	62.7	66.9
STD [1]	1.4	3.8	3.0	11.5	8.7
Max [2]	6.0	12.0	30.0	74.0	79.0
Min [3]	1.0	3.0	22.0	35.0	50.0

[1] Standard deviation [2] Maximum value [3] Minimum value.

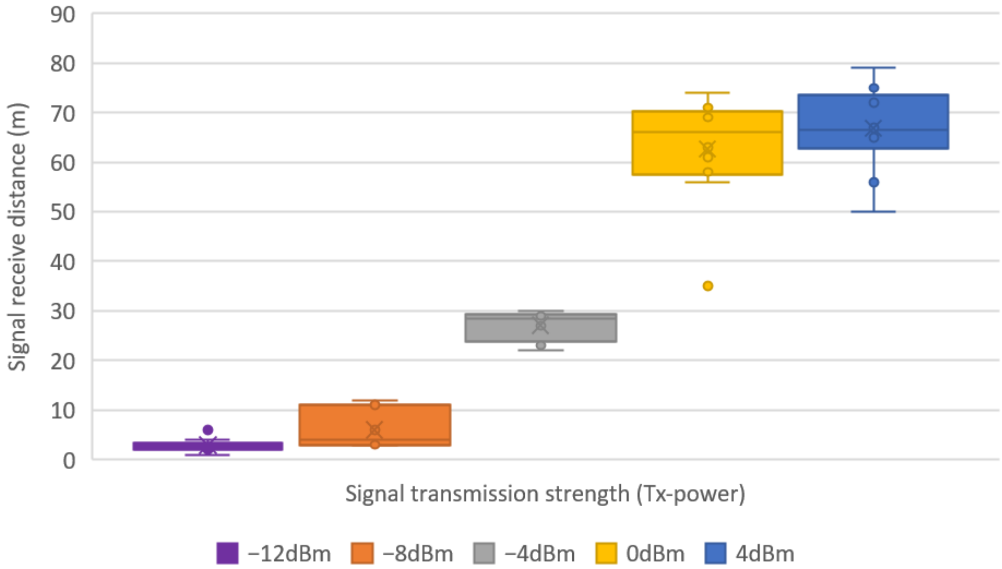


Figure 10. Average BLE signal detection distance of smart helmet according to Tx power of Bluetooth beacon (m).

Table 5 shows the statistics of the sensing distance measurement when a proximity alarm was provided according to the facing angle between the smart helmet and the Bluetooth beacon, and Figure 11 shows the average sensing distance per angle. The average sensing distance was measured to be over 20 m for angles of 0°, 45° and 90°, approximately 20 m for an angle of 135°, and 10 m for an angle of 180°. Therefore, it was confirmed that the average BLE signal detection distance was at least 10 m, regardless of the facing angle between the smart helmet and Bluetooth beacon.

Table 5. Statistical analysis results of the BLE signal detection distance (m) of the smart helmet according to the facing angle between the smart helmet and Bluetooth beacon.

BLE Signal Recognition Distance (m)	Facing Angle between the Smart Helmet and the Bluetooth Beacon (Degree)				
	0°	**45°**	**90°**	**135°**	**180°**
Mean	27.1	25.1	22.8	19.4	10.0
STD [1]	3.0	4.7	6.6	5.9	4.3
Max [2]	30.0	30.0	31.0	29.0	15.0
Min [3]	22.0	18.0	9.0	13.0	4.0

[1] Standard deviation [2] Maximum value [3] Minimum value.

Figure 12 is a radial plot of the average value of the scores of the six workload parameters evaluated in three experiments for four types on 10 subjects. When the subjects used a smartphone-based personal PWS, scores on mental demand, time demand, physical demand, frustration, effort, and overall performance were all higher than when using a smart helmet-based personal PWS. This may be due to the fact that when a subject used a smartphone-based personal PWS while driving, they had to repeatedly check the smartphone screen to check whether the worker was approaching the vehicle and felt apprehensive due to increased eye movement. Conversely, when using a smart helmet-based personal PWS, the subjects could concentrate only on driving and receive a visual alert through the LED light of the smart helmet worn by the worker; therefore, both hands were relatively free compared to when using a smartphone-based personal PWS. Consequently, less workload is required to perform the task. Similar to using a smartphone-based personal PWS, when workers wore smart glasses-based personal PWS, mental, physical, and frustration scores were higher than when wearing smart helmet-based personal PWS. In particular, the frustration score differed the most because they were unfamiliar with wearing smart glasses (glasses slipping and wearing ordinary glasses under smart glasses), whereas the feeling of wearing a smart helmet was similar to that of a general safety helmet.

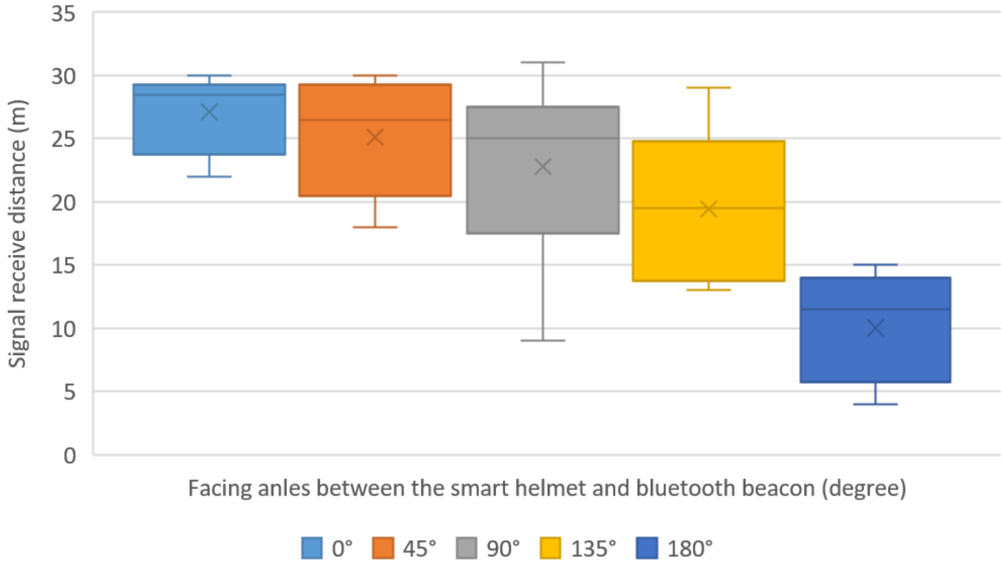


Figure 11. Average BLE signal detection distance of the smart helmet according to the facing angle between the smart helmet and Bluetooth beacon (m).

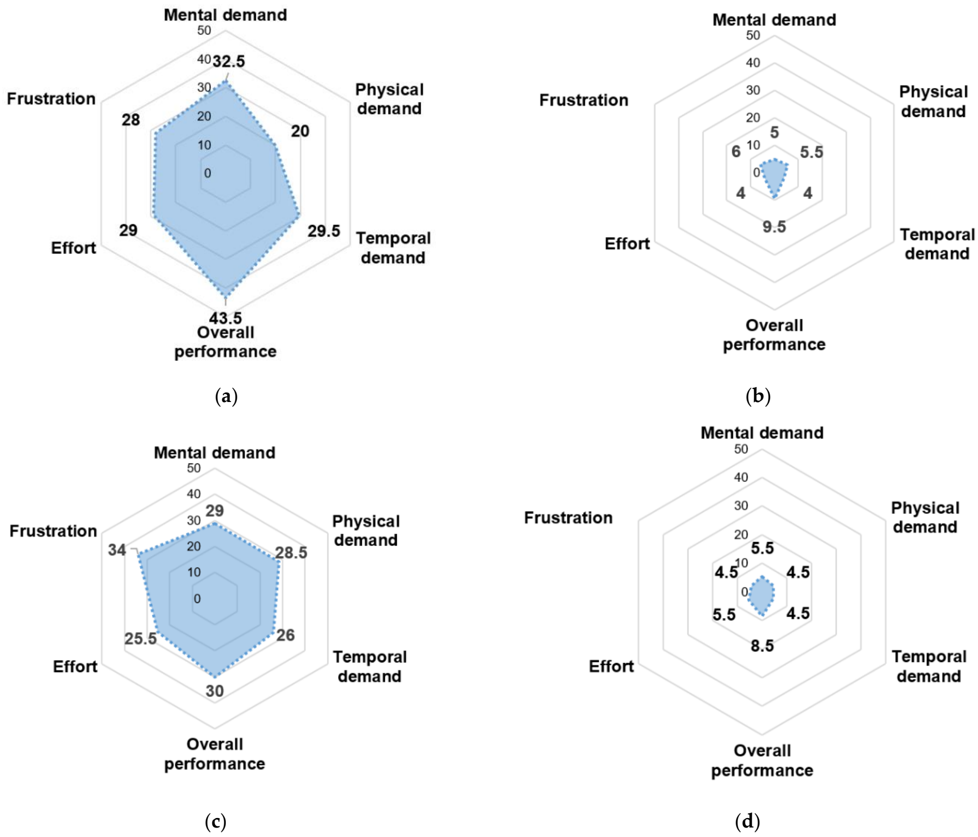


Figure 12. Average value of the evaluation scores of the six workload parameters of the NASA-TLX according to the type of experiment. (**a**) Type 1: workload of truck drivers when using the smartphone-based PWS; (**b**) Type 2: workload of the truck drivers when using the smart helmet-based PWS; (**c**) Type 3: workload of the pedestrian workers when using the smart glass-based PWS, and (**d**) Type 4: workload of the pedestrian workers when using the smart helmet-based PWS.

Figure 13 shows the total workload score calculated in the four experiments divided into the driver side (a) and the pedestrian side (b). The drivers who used the smartphone-based personal PWS scored approximately 32 points, whereas drivers who used the smart helmet-based personal PWS scored approximately 6.3 points. Workers using the smart glasses-based personal PWS scored approximately 30.6 points, whereas workers using the smart helmet-based personal PWS scored approximately 5.9 points. The smart helmet helped to increase work efficiency by effectively providing proximity warnings for equipment or vehicles to the driver and worker simultaneously while freeing both hands of the driver and worker. Moreover, compared to smart glasses, the wearability of the smart helmet was convenient, which helps reduce worker stress.

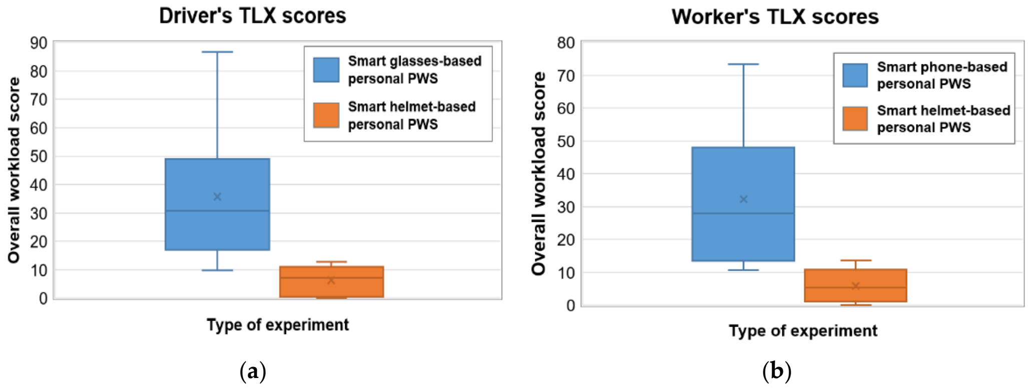


Figure 13. Results of the overall workload score assessment. (**a**) Overall workload score according to the type of experiment on the driver side; (**b**) overall workload score according to the type of experiment on the pedestrian side.

5. Discussion

5.1. BLE Signal Propagation in Underground Mines

In underground mines, there are several structural and environmental factors that cause diffraction, reflection, and interference of BLE signal propagation. For example, there exist excavations with crossings inclined at 90 degrees and curved sections. These structures make stable line-of-sight propagation impossible. The mine wall has a high roughness that causes diffraction and reflection of the signal. In addition, radio signal attenuation occurs due to the rock mass. All mine areas have high relative humidity, and dust particles are suspended in the air. Electrical installations for power supply exist throughout underground mines. As a result, signal interference may occur due to electromagnetic fields. Therefore, it is necessary to perform BLE signal testing to understand the effects of disturbing factors that interfere with stable BLE signal propagation in underground mines.

5.2. Advantages of Smart Helmet-Based PWS

Personal PWSs using a smart helmet have the following notable advantages at the mining site. First, this system can solve the problems that occurred in existing PWSs. The driver had to repeatedly check the smartphone to receive the proximity warning alerts. It caused a decrease in the operators' concentration on driving. Smart glasses caused discomfort when workers wore regular glasses or when they slipped. On the other hand, smart helmets can provide visual proximity alerts to both the operator and the pedestrian without work interruption, enabling quick identification of dangerous situations and quick evacuation. Workers who are wearing regular glasses, industrial goggles, and soundproof headsets can also wear smart helmets without discomfort.

Second, smart helmet-based PWS is relatively easy to use for workers. Operators and workers who use existing PWSs need to operate a touchpad controller to execute PWS application. However, subjects who participated in the NASA-TLX test tended to feel difficulty in such an operation. On the other hand, the smart helmet-based PWS is a relatively convenient and easy to execute system because only a power supply is required.

Finally, the proposed personal PWS can be implemented and utilized in the mining site at a relatively low cost. Since this system utilizes Arduino, an open-source hardware, relatively low cost is required to constitute system components (i.e., microcontroller board and sensors). Therefore, it is possible to distribute multiple sets of smart helmets and Bluetooth beacons to the worksite, regardless of the size of the mine.

6. Conclusions

In this study, we developed a personal PWS that uses a smart helmet to receive BLE signals from Bluetooth beacons and provides visual proximity alerts to pedestrians and equipment operators. The smart helmet-based PWS could provide bidirectional proximity warnings to equipment operators and pedestrians in mines. A performance evaluation was conducted at an actual underground mine site to evaluate the performance of the personal PWS developed in this study. The BLE signal detection distance of the smart helmet was measured according to the Tx power of the Bluetooth beacon and the facing angle between the Bluetooth beacon and the smart helmet. The average BLE signal recognition distance was 2.9 m at −12 dBm, 6.0 m at −8 dBm, 27.1 m at −4 dBm, 62.7 m at 0 dBm, and 66.9 m at 4 dBm. As the Tx power of the Bluetooth beacon increased, the BLE signal recognition distance of the smart helmet increased. In addition, when considering the facing angle between the smart helmet and Bluetooth beacon with a Tx power of −4 dBm, it was confirmed that the average BLE signal detection distance was at least 10 m regardless of the facing angle. The workload of the individual PWS for 10 subjects was quantitatively analyzed using the NASA-TLX evaluation method. The use of smart helmets to provide visual proximity alerts reduced mental effort and stress, and freed the hands of workers to maintain work efficiency. The overall workload score calculated when using the smart helmet was lower than when using the smart phone-based PWS and the smart glass-based PWS. Therefore, a smart helmet is suitable for implementing personal PWSs at the mining site.

In future work, smart helmet-based personal PWS can be expanded by adding sensors to the Arduino board. For example, a heart rate sensor or an alcohol sensor can be added to check the condition of the worker. Furthermore, by adding a temperature, humidity, methane gas, and carbon monoxide sensor, the environment at the mine site can be monitored, and when a high concentration of harmful gases is detected, the pedestrian worker can be warned of danger. The worker could then follow appropriate protocols to ensure safety.

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