Smart Plants on Wheels: Enhancing Indoor Productivity using Smart Plants and Autonomous Ground Drones

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***Abstract*—*Smart plants*, sensor-equipped plant containers, are emerging as a promising solution for monitoring indoor environments and human activities. The plant containers are usually strategically placed close to areas where people typically spend time with the aim of enhancing indoor quality, satisfaction, and comfort. We contribute an innovative concept, smart plants on wheels, that integrates smart plant containers with autonomous ground vehicles (AGVs) allowing them to move between different areas within a workspace. By doing so, we aim to foster improved well-being and work productivity. To demonstrate our concept, we have built a proof-of-concept prototype. Additionally, we explore applications and research challenges to establish a broader research agenda. In a user study involving $N = 24$ participants, we found that our concept significantly enhances productivity in a real working environment. Specifically, we are able to accelerate response times by up to 32% (in complex cases).**

***Index Terms*—Pervasive-Sensing; Cooperative-Robots; IoT; Unmanned-Vehicles; Service-Robot**

I. Introduction

Productivity at work is linked with satisfaction with the ambient conditions of indoor spaces [1], human cognitive changes [2], and an individual's personality traits [3]. Sensors embedded into the environment can analyze characteristics of the environment and the individuals residing in it with, which can be used to enhance productivity and help optimize the indoor environment [4]. Indeed, there already are successful examples of how pervasive, wearable, and smartphone technologies can enhance productivity, e.g., by facilitating users to reduce time spent on non-work activities [5], by using sensors to monitor and improve indoor comfort, and by improving the quality of indoor air.

Plants have been found to boost indoor productivity, to reduce stress levels, and to increase the well-being of individuals [1]. Individuals interacting with plants can benefit from increased happiness levels, improved positive attitudes and enriched ambient comfort [3]. Nowadays, plants can be *smart*, meaning the containers housing them are integrated with sensors. *Smart plants* are type of plants where the containers housing the plant are integrated with sensors [6]. These sensors can be used to reduce their maintainability and to maintain the plants, e.g., by monitoring soil and optimizing watering schedules. While the intended purpose for the sensors is to monitor and optimize plant growth conditions, the sensors can also be a powerful source of information on the activities that happen in the plant's proximity. For example, smart plants can be used to count people and to detect compliance with mask use restrictions [6]. What makes smart plants particularly interesting as a sensor is that they do not need to be installed but can be deployed simply by placing the containers in the space. In this paper, we envision that the interactions between people and plants could be further harnessed to enhance productivity and well-being within an indoor environment.

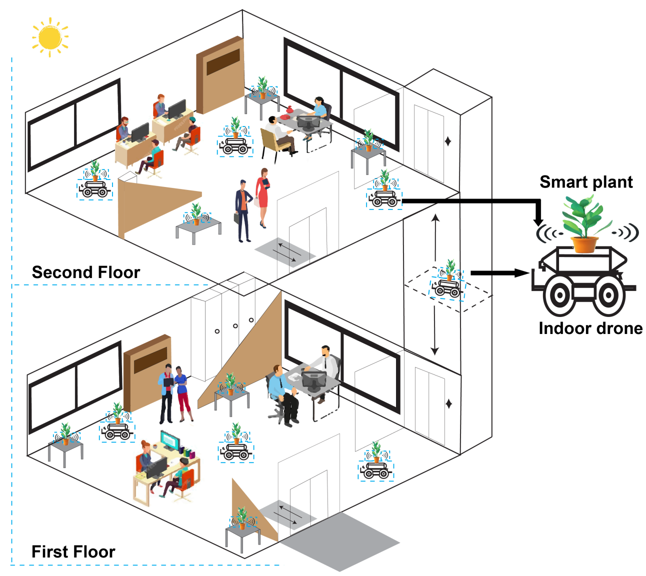


Fig. 1: Vision of smart plants on wheels moving and adapting to indoor building conditions and users.

We contribute *smart plants on wheels* as an innovative concept that combines smart plants with indoor-autonomous ground drones. This allows adapting the plant's location to the occupant and the environment, while allowing novel human-plant interactions through voice-command-based control. Autonomous drones are already a practical solution for many everyday environment [7]. Our concept, illustrated in Figure 1, can harness the sensors on smart plants to trigger the drones to move the plant to a new location, and instigate the users to interact with the plants. The users, in turn, can use voice-commands to interact with the drones and enable activities that affect the plants. Note that plant mobility not just benefits the individual user, but can also be used for other purposes, e.g., to optimize plant growth conditions. For example, the plants can automatically move to a side where sunlight is more prominent, or move closer to a watering area when they start to dry up. We present a proof-of-concept prototype designed and constructed using rapid prototyping and off-the-shelf devices. In a user study with $N = 24$ participants, we show our concept can enhance indoor productivity in a real working environment. Specifically, moving the plants in and out can enhance the participant's performance in cognitive tasks (13% improvements in low-complexity tasks and up to 32% improvements in high complexity tasks). Additionally, we explore application areas and research challenges to establish a broader research agenda. Our work paves the way for innovation smart plant and drone solutions to improve indoor environments and enhance productivity.

II. Related work

Personal robots, follow-me devices and productivity: Drones can be used to boost human productivity, as has been shown in studies ranging from exercise support to security surveillance [8]. IoT devices integrated with drones and vehicular technologies have tracked and followed ground targets, aiding in security and surveillance, while also used for aerial photography and video capture. Personal robots like the "PlantBot" and desktop robot integrate with users' everyday lives to improve mental health and productivity [9], [10]. Our work offers a new approach where an indoor (ground) autonomous drone is used to support plant mobility with the aim of enhancing the quality of the indoor environment and human productivity.

Smart plants: Research has demonstrated that plants in indoor spaces offers many benefits from user comfort to improved well-being [11]. Plants have been equipped further with sensors, resulting in reduced maintenance requirements and an enhanced understanding of the environment [6]. For instance, smart plants have been integrated into indoor spaces to gather occupancy data and even detect the utilization of protective face masks [6]. Autonomous mobile robots have also been augmented with IoT sensors to efficiently oversee and maintain the health of plants [12]. Similarly, sensors have been discreetly embedded within potted plants, enabling comprehensive data collection regarding the plant's condition. Unlike previous work, we propose a system that combines smart plants with indoor autonomous ground drones to facilitate the mobility of the plants indoors and to encourage user interactions with plants.

III. Smart Plants and Productivity

Our work focuses on using smart plants and autonomous ground drones to foster productivity, and to enable new types of human-plant interactions. We next briefly highlight some emerging applications that can benefit from our approach.

Team work applications: Object sharing and shared responsibility are potential ways to improve collaborative work practices. Smart plants integrated with indoor AGVs can benefit from the principles underlying multi-device sensing – the sharing of resources to augment the capabilities of individual devices – and establish networks where the object to be shared is the smart plant. By fostering shared plant maintainability, it is possible to reinforce a collaborative environment and to foster a more productive work environment.

Creativity support: Sensors instrumented within the smart plant containers can monitor and characterize the blooming cycles of the plants. Plants that are at the peak of their blooming cycle tend to be lusher and fresher, and they have potentially the largest benefits to human productivity. In fact, according to studies conducted at workplaces, individuals that are exposed to the color green for a brief period of time just before carrying out a task can receive a substantial boost on productivity, which is known as the green effect [11]. Indoor AGVs can be used to optimize the routes and schedules of plants so that they align with the start of a task. Alternatively, mood and cognitive load monitoring solutions available on smartphones [13] can be used to detect periods where individuals would most benefit from plants and the AGVs can be used to guide the plants to individuals that would most benefit from them.

Take-a-break applications: Personal devices can be equipped with applications that can be used to track sitting time at work and to suggest stretching breaks. Some smartphone apps, such as Pomodoro, rely on timing intervals to suggest when to work and when to rest. These approaches have shown to be effective at improving productivity. Plants can replace the role of personal smart devices and provide a less privacy intrusive solution for monitoring work burdens. Through voice interaction, they can also offer rest and stretching activities that are better tailored to the work space.

IV. Smart plants on Wheels: Prototype Design

We have developed a proof-of-concept prototype of a smart plant container that has been integrated with an AGV. Our design has been constructed using rapid prototyping and serves as an early stage proof-of-concept design to demonstrate the potential of our concept. In the following we detail the different components of our prototype design.

Apparatus: The prototype design is shown in Figure 2 and relies on off-the-shelf components designed for rapid prototyping. The smart plant is embedded with sensors for soil moisture (Capacitive Moisture Sensor), air temperature and humidity (DHT22), and ambient light (APDS 9660 sensor). As indoor AGV, we use the DFRobot- Analog. The smart plant container is placed on top of the AGV, and a smartphone is mounted on the AGV to offer processing support and off-the-shelf speech recognition functionality.

Integration: The core elements encompass a microcontroller board (`LOLIN_WEMOS_D1_R2-mini`), a power distribution

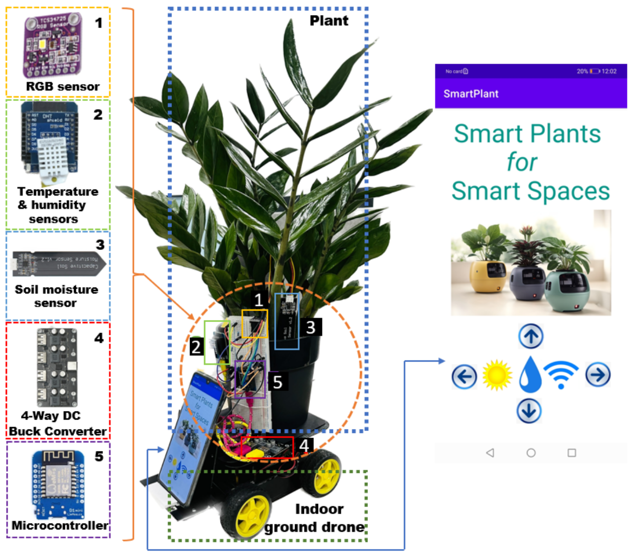


Fig. 2: Smart plants on wheels prototype.

unit (`4-Way DC BuckConverter`), and sensors. We employ a soil moisture sensor capable of measuring the water content in the soil, an RGB light intensity sensor to measure the intensity of light in the vicinity, and temperature and humidity sensors to assess the environmental conditions. Collected data is uploaded to a web server running in the phone using HTTP payload. To interconnect the components in our prototype, we use a hub-type architecture where a smartphone acts as an intermediary for connecting the plant with the drone. This is due to the drone offering limited programmability, and the smartphone offering sufficient storage and computational power to store and process the sensor data. The smartphone also offers a simple voice command interface that allows controlling the movements of the drone (one of four directions: up, down, left and right, relative to the drone).

Cost: The total cost of our prototype is approximately 285 euros with the components in the smart plant container costing $\approx$ 100 euros, and the remaining $\approx$ 185 euros covers the drone costs. The micro-controller, connectors and sensors that support the computing and sensing functionality altogether have a cost of 100 euros (Micro-controller $\approx$ 40 euros, BuckConverter $\approx$ 35 euros and Sensor-kit $\approx$ 25 euros). The cost of the drone chassis is $\approx$ 185 euros. Our prototype is built to support plants with dimensions, height =33 cm, width =22.5 cm and weight =2.5 kg. Thus, bigger plants require large drone chassis, which may increase the overall cost. The in-built voice command functionality is supported by old discarded smartphones, having no cost in our prototype. This price falls within reasonable levels for robot automation solutions for homes and offices. For instance, latest ROPVACNIC Robot Vacuum Cleaner has a cost of 350 euros, whereas iRobot Roomba 694 Robot Vacuum-Wi-Fi has a cost of 230 euros. Naturally, when manufactured at large-scale, we expect the cost of our smart plants on wheels to be reduced significantly.

V. Benefits of Smart Plants on Wheels: Experimental Setup

We next report on two experiments that highlight uses of our concept and demonstrate their benefit in enhancing work productivity. The first experiment uses the sensors on the plant containers to characterize the surrounding environment, and the second experiment demonstrates that smart plants on wheels can enhance work productivity by reducing cognitive load. We next detail the experimental designs.

Experiment #1: Sensing and Interactivity Performance: The first experiment analyzes the performance of the sensing and interactivity components in our prototype with the aim of understanding whether the integration of sensors into the plant container or with the drone affect the sensor measurements. Sensing performance is an important factor for productivity whereas interactivity is critical for controlling the mobility of the smart plants. We deploy our prototype in an office environment that has constant ambient light (300 LUX, measured with a smartphone), consistent air conditioning, and stable temperature. We use the prototype to collect air temperature, humidity, and light intensity measurements over seven working days. These measurements are commonly used to estimate productivity [14]. As part of this study, we also evaluate the performance of the voice interaction module to understand its potential to support human-plant interactions. We recruited 18 participants (12 male and 6 female) to analyze interactivity. The participants were aged between 22 and 39 years, with an average age of 30.56$\pm$3.9 years. The experiment consists of detecting three types of commands, a) simple, b) complex and c) concurrent. Simple commands depict moving actions, including “move up”, “ move down”, “ move left”, and “move right”. Complex command consists of natural sentences that include a basic command. For instance, “Hey, smart plant, move left”. Concurrent commands are complex commands given by simultaneous users. Each participant evaluated 10 sequential commands for the simple and complex case. Lastly, five participants were asked to perform the concurrent command experiment.

Experiment #2: Cognitive Load: The second experiment measures the direct effects our concept can have on productivity by assessing cognitive load with and without exposure to plants. 24 participants are recruited, consisting of 15 males and 9 females, with age ranging from 23 to 53 years (average age of 33.25 $\pm$ 6.78), comprising of University of Tartu employees. Participants are divided into two groups, those with exposure to plants (Group 1) and those without (Group 2). The experiment was conducted over seven working days. Participants provided consent for participation, following internal ethical regulations. Figure 4(a) shows the experimental design. Both groups were subjected to a cognitive load task in the morning without having exposure to the plant. This serves as a control condition for comparing the response across the two groups. The cognitive load was measured using the Stroop test which measures working memory and attention [4]. The test comprises two kind of trials: congruent and incongruent. In incongruent trials, color names, such as ”red,” were presented in a different color (e.g., ”green”), challenging the participants’ cognitive processing. Congruent trials involved presenting color names in matching colors. Additionally, we introduced a third set of trials (unrelated) where non-color words (e.g., ”xbrq”) appeared in various colors. Cognitive performance was measured based on number of errors and the response time for each trial. Once the participants had answered the test, for participants in Group 1 the plant was then moved to within 5 meters of the subject, highlighted in the experimental design, and remained in the same location throughout the day. In contrast, participants in Group 2 had no exposure to the plant. In the afternoon, both groups repeated the test approximately two hours after the first task. A random offset was used to make the test timings less predictable.

VI. Results

A. Sensing Performance

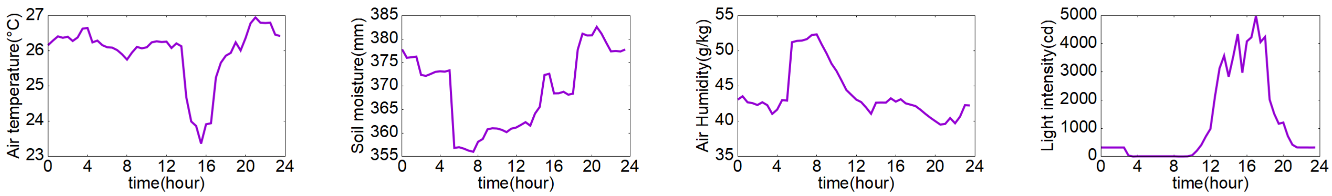
The measurements collected with the smart plant sensors are shown in Figure 3. The values in the figure correspond to averages across the one week period. The first observation is that the sensor values accurately capture characteristics of the environment and detect events affecting these characteristics. For example, the temperature values are mostly consistent, remaining at around (around 26 degrees Celsius) with the exception of around 2pm where the heating automatically switches off for a short period to preserve energy. Similarly, the light intensity measurements are in line with common office hours, remaining low during the night and late evenings. Additionally, the peak in luminosity values between 12:00 pm and 8:00 pm suggest the plants may be actively moving closer to an open windows during these hours. This behavior aligns with plant's inclination to seek direct exposure to sunlight, which is vital for their growth and overall health. The humidity values contain slightly higher variation, but remain within regular levels of a healthy indoor environment (30 - 60%). All of these parameters are linked with productivity, with temperature and humidity also affecting thermal comfort [14] which is an important parameter for assessing the well-being of the individuals within the space. While not the aim of this study, the ground drone can also be used to move the smart plant close to a window to capture ambient sunlight intensity. This parameter is used to estimate thermal comfort and thus the plant mobility offers opportunities to sample environmental parameters within the indoor environment. Finally, the measurements reflect changes in weather outside the office. The measurements show changes that align with weather conditions. For example, humidity peaks in the early morning due to rainfall. Outside weather can affect productivity, e.g., studies suggest that bad weather may enhance productivity [15]. Our approach detects these conditions and can help enhance productivity by relocating the smart plant. The results also reveal one issue, however, as the accuracy of the soil moisture measurements is poor. This is likely due to the drone's movement, but can also be affected by the drone's location. Nevertheless, as the analysis shows, the sensors provide valuable insight into environmental conditions and productivity-related parameters.

B. Interactivity Performance

In the simple command case, 90% of commands from different users are detected accurately. For complex commands, the performance drops slightly, but is good overall (87.5% accuracy). This suggests that the off-the-shelf speech recognition tools are sufficient for interactions with a single user. In contrast, with concurrent commands, the prototype fails to recognize any commands. Thus, multi-user interactions require better support tools to be feasible. Note that in multi-user interactions we also need to consider the impact the commands may have on other people in the environment. For example, a command to move should not be followed when the drone is surrounded by people even if the command is recognized correctly. Another implication of this result is that coordinating the actions in multi-user environments may require identifying the user that is issuing the command first. Nevertheless, as the results show, the performance is more than satisfactory to single user scenarios even if further research would be needed for multi-user environments.

C. Cognitive Load

The results of the cognitive load experiments are summarized in Figure 4. The plot contains the response time of the participants in both groups during the control condition (morning) and during the test situation where the groups differ in terms of their exposure to the plant (Group 1 observes the plant, Group 2 does not observe the plant). Firstly, as expected, the results for congruent (low complexity) tasks are consistently faster than those for incongruent (high complexity) tasks. This simply confirms that the experiment works as intended. Second, we observe that during the morning, the groups have generally similar performance with the only differences being a result of variations in the individuals. Indeed, no significant differences across the groups can be observed. Third, once the participants in the first group are exposed to the plant prior to the task, their performance significantly improves compared to the second group. The mean response time for congruent trials decreases from 23.9 seconds to 21.1 seconds ($13,3\%$ improvement) for the congruent trials and from 40.2 seconds to 30.5 seconds ($31,7\%$ improvement) for incongruent trials. Thus, the higher the cognitive demand, the bigger the improvement in response time. To further validate these observations, we used the Welch two-sample T-test between the groups to compare the differences in the different conditions. For the tests carried out during the morning, i.e., the control condition, there were no statistical differences in completion times during congruent (Group 1 = 21.05 ± 1.63, Group 2 = 20.93 ± 1.97, T = 0.23, p-value = 0.82) and incongruent trials (Group 1 = 31.00 ± 1.62, Group 2 = 30.27 ± 1.82, T = -0.74, p-value = 0.32). In contrast, for the afternoon tests, the two group conditions indicate a statistical difference in response time completion for both, congruent trials (Group 1 = 21.06 ± 0.89, Group 2 = 23.93 ± 1.92, T = -4.7, $p < 0.05$) and incongruent trials (Group 1 = 30.58 ± 1.94, Group 2 = 40.18 ± 4.13, T = -7.2, $p < 0.05$). These results indicate that moving plants closer to users can indeed enhance productivity,



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

Fig. 3: Smarts plant sensor results: (a) Air Temperature (b) Soil moisture (c) Humidity (d) Light intensity

in line with prior studies [11]. As both groups were subjected to the same study twice, the participants can be expected to be primed and thus their performance should be higher in the afternoon than in the morning. Yet, only those exposed to the plant had significant changes in their cognitive performance, further supporting our findings. Unlike existing works, we offer a practical solution that can be used to move the plants around the indoor environment to achieve the desired effects in productivity.

VII. The Path Forward: Challenges and Opportunities

Our study identified two key benefits of smart plants on wheels: environmental productivity monitoring and reducing cognitive load. While our concept has potential beyond these benefits, addressing technical challenges is necessary to fully realize it. We next discuss some of these challenges going forward.

Human - smart plant interactions: The use of drones as a platform for smart plants on wheels offers mobility. Likewise, voice interaction is used to control the movements of the drones [16], allowing occupants to manage plant mobility. Other interaction methods, such as gesture control via camera-based solutions or ultrasound sensors, can also be supported. Advanced voice interactions can leverage large language models like ChatGPT or Llama for more complex operations [17]. Sensors on the plants can inform users when watering is needed or suggest optimal locations where plans may be needed. A key challenge is to make interactions between smart plants on wheels and humans more natural and user-friendly.

Productivity planning strategies: While plants alone can enhance productivity [1], more sophisticated approaches can sustain this boost over time. As the impact of stationary smart plants declines, their mobility can be used to maintain productivity by relocating them based on cognitive factors and user mood. Smart plants can be grouped and positioned to improve mood or support comfort and aesthetics, such as moving them next to a window for sunlight while minimizing heat [18]. The main challenge lies in designing strategies to schedule and redeploy smart plants efficiently.

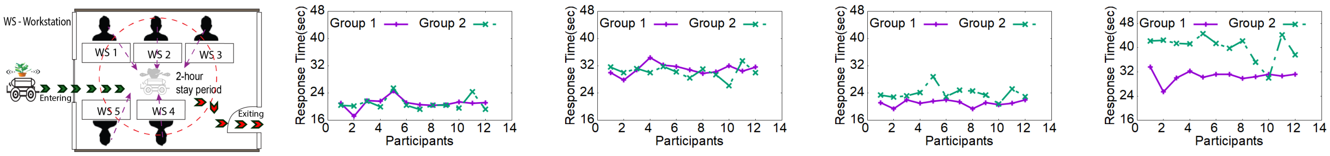
Authentication and secure interactions: Detection of a user (owner or valid user) becomes a critical challenge when interacting with smart plants. The mobility of smart plants could become a problem if smart plants can take commands from any user. For instance, blocking indoor areas and moving randomly between indoor locations. A way to overcome this is to foster collaborative swarm methods between smart plants [19], such that they can regulate by themselves based on the indoor policies of the building. For instance, not more than 10 plants in the meeting room at once. Besides this, authenticating users becomes important as smart plants have a number of integrated sensors that can be used for human surveillance. Smart plants could provide a way to monitor indoor environments easily unless they are better safeguarded [6].

Trustworthy smart plants: Efficient operations of indoor AGVs are achieved through the use of machine and deep learning models, e.g., for navigation and obstacle detection [12]. Deploying indoor AGVs close to the user requires accounting and certifying the AI models that are used in these functionalities. Human - smart plant interactions can also lead to the collection of private sensitive data. Given the regulations of EU GDPR and the US AI Act on the use of private data and AI training; it is a key challenge to develop tools and procedures to monitor and tune the AI functionality of smart plants.

Recurring issues: Several issues are recurring over time and others are inherent to specific technologies. Battery of indoor AGVs is a key limitation for the adoption of smart plants. This problem is easier to solve indoors as there are plenty of alternatives that can be adopted. For instance, wireless charging could alleviate the continuous charging problem of indoor AGVs. Another key challenge is the accuracy of sensors used within smart plants. Sensors could be easily damaged or provide measurements with high errors that could yield damage to plants. Calibration and compensation methods to deal with errors are required to overcome this problem. However, it may be that the sensor has to be calibrated based on the type of the plant and other characteristics of it, e.g., type of soil. As a result, a key challenge is to develop compensation methods that can generalise the sensors across differing plants.

VIII. Discussion

Further improvements: The smart plant prototype can be further improved by integrating thermal arrays, air quality sensors, and other sensors that provide information about the indoor environment. This information can then be used to design more complex interactions and strategies, e.g., plants could be relocated during indoor meetings to improve comfort and reduce CO_2 levels. The plant interactions can be further enhanced by taking advantage of LLMs and improved speech recognition to offer more natural interface and enable new interactions, e.g., to deliver messages or to delegate plant



(a) Testbed (b) Congruent-before (c) Incongruent-before (d) Congruent-after (e) Incongruent-after

Fig. 4: Cognitive load on task completion, a) In and out deployment of smart plants on wheels; b)-c) Morning evaluation; d)-e) Afternoon evaluation.

maintenance. Finally, the drone movement can be further enhanced by integrating better navigational support, obstacle detection, and other related functions supported by AI models.

Subjective productivity: The experiments demonstrated how moving plants close to people can help improve productivity and reduce cognitive demands. Naturally, plants are not the only factor affecting productivity as individual traits (age, demographics, mental health, personality etc.) [20] also have significant effect. By integrating more sensors and better interaction capabilities, the plants can be made more context-aware and personalized. This allows personalizing and adapting the actions to different users and environments. Nevertheless, our work shows that smart plants integrated with ground drones can serve as a base solution for enhancing productivity.

On traversing buildings: Indoor AGVs have difficulty moving between different floors. While lifts and doors can be instrumented with sensors to open as the indoor AGV approaches, not all lifts can be instrumented easily, requiring modification of building characteristics to adopt this technology transparently. A way to overcome this is to rely on opportunistic human movement and take advantage of moments when humans open the doors.

IX. Summary and Conclusions

We presented smart plants on wheels as an innovative concept that combines smart plants and indoor AGVs to help foster and increase the productivity of individuals. While smart plants integrate sensors to monitor their growth and health – and the environment to some extent – by granting smart plants the ability to move, it is possible to exploit their natural attributes to improve productivity at work. We demonstrated this by designing an early prototype and carrying out experiments that demonstrated how the prototype can be used to monitor the environment and improve the user's cognitive performance (up to 31% improvements, depending on task complexity). We also highlighted open research challenges and opportunities that need to be full-filled to take our vision forward.

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