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Potential of mobile applications in human-centric production and logistics management

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Abstract: With the increasing market penetration of smart devices (smartphones, smartwatches, and tablets), various mobile applications (apps) have been developed to fulfill tasks in daily life. Recently, efforts have been made to develop apps to support human operators in industrial work. When apps installed on commercial devices are utilized, tasks that were formerly done purely manually or with the help of investment-intensive specific devices can be performed more efficiently and/or at a lower cost and with reduced errors. Despite their advantages, smart devices have limitations because embedded sensors (e.g., accelerometers) and components (e.g., cameras) are usually designed for nonindustrial use. Hence, validation experiments and case studies for industrial applications are needed to ensure the reliability of app usage. In this study, a systematic literature review was employed to identify the state of knowledge about the use of mobile apps in production and logistics management. The results show how apps can support human centricity based on the enabling technologies and components of smart devices. An outlook for future research and applications is provided, including the need for proper validation studies to ensure the diversity and reliability of apps and more research on psychosocial aspects of human-technology interaction.

Keywords: App, Mobile application, Smart device, Human factors, Systematic literature review

1. INTRODUCTION

In recent years, the burgeoning development of mobile applications (apps) has caused them to permeate an increasing number of aspects of daily life. It has been reported that approximately 1.85 million apps are available for users to download and use in the iOS App Store and 2.56 million in the Google Play Store (Iqbal, 2022). In recent years, engineers have also started to develop various applications for industrial use. In such tasks as assembly (Minnetti et al., 2020), maintenance (Kleiber et al., 2012), and order picking (Grzeszick et al., 2016), apps have been developed to utilize sensors and components of commercial smart devices to support human operators. In general, this support can also be provided by devices specifically developed for industrial use. However, the advantages of applying commercial smart devices (such as smartphones, smartwatches, and tablets) are that these devices are used by most operators anyway, and the operators are already familiar with these devices through daily private use. Applying them in industrial environments can reduce investment costs in device acquisition and system setup and may lead to higher operator performance (e.g., Flatt et al., 2015). In addition, these devices are easy to carry for operators, creating the potential for real-time notification or emergency management (e.g., Depari et al., 2018). A systematic overview of these advantages in the industry — in particular, how apps can support human-centric (in terms of perceptual/mental, physical, and psychosocial aspects according to Glock et al., 2021) production and logistics management — is lacking. Therefore, a systematic literature review was conducted to 1) identify the enabling technologies behind the mobile apps used in production and logistics management, and 2) analyze these applications from a human-centric viewpoint to define future research opportunities.

Several literature reviews on related topics are available, and they are briefly discussed in this article. As a key enabler of mobile apps, smartphone sensors provide basic functionalities. Lane et al. (2010) reviewed research on embedded sensors, such as accelerometers, gyroscopes, microphones, and cameras, and proposed a mobile phone sensing architecture. Grossi (2019) conducted a comprehensive survey of smartphone measurements and sensing functions. However, these studies did not focus on the industrial domain. Other reviews have been conducted to evaluate the use of smart devices in specific applications, including human activity recognition (Incel et al., 2013; Reining et al., 2019; Demrozi et al., 2020), indoor positioning (Mendoza-Silva et al., 2019), and augmented reality (Bottani and Vignali, 2019; Glock et al., 2021). In addition to smartphones, other commercial devices, such as smartwatches, can support human operators. Nascimento et al. (2020), for example, conducted a review on how utilizing smartwatches and installed apps supports gesture

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recognition. These studies showed that, when smart device sensors are used, various tasks that were formerly handled manually or with the help of special devices can be performed more efficiently and/or at a lower cost. As concluded by Aceto et al. (2019), smartphones and other smart devices are key enablers of Industry 4.0. Despite these previous literature reviews, to the best of the authors' knowledge, no study has been conducted on the potential of apps run on smart devices in production and logistics management. The contributions of this research can be summarized as follows. First, focusing on mobile apps, articles were selected, including validation studies, that show various types of support in different functions in industrial processes. The findings provide an overview of ready-to-use industrial supporting apps for researchers and practitioners. Second, the support is classified from a human-centric viewpoint, the current research gaps in the literature are identified, and the need to develop apps for supporting human operators in different aspects is emphasized.

The remainder of this article proceeds as follows. The review methodology is described in detail in Section 2. In Section 3, the sampled articles, categorized by their enabling technologies, are described, followed by the human-centric analysis in Section 4. Finally, Section 5 provides the conclusions.

2. METHODOLOGY

To gain insight into the state of research on app-supported production and logistics management, the literature was reviewed systematically. First, a search string was developed and grouped into two sets. Group A consisted of keywords related to apps and smart devices, and Group B was related to fields of application. The detailed search strings are presented in Table 1.

Table 1. Keywords used in the SCOPUS search

Keyword group A
"mobile app*"; "android app*"; "ios app*"; "smartphone app*"; "phone app*"; "smart app*"; "smart phone*"; "smartphone*"; iphone; "tablet computer*"; "tablet personal computer*"; "tablet pc"; "tablet device*"; "handheld tablet*"; ipad; "smart watch*"; "smartwatch*"
Keyword group B
Single word subgroup: warehous*; "order picking"; "internal logistic*"; Material handl*"; troubleshooting **Phrase subgroup 1:** production; maintenance; manufacturing; assemb* **Phrase subgroup 2:** line*; system*; process*; procedure; plan*; task*; strategy; engineer*; activit*; operation*; staff; team*; worker*; cost*; failure*; data; time

Within each keyword group, the Boolean operator "OR" was applied, whereas the two groups were combined with the "AND" operator. Group B consisted of two parts. Each word in the "single word subgroup" appeared independently in the search string, whereas each word in "phrase subgroup 1 & 2" was combined with every single word in the other subgroup to formulate phrases — for example, combining "production" and "line*" results in "production line*" — where the objective was to describe precisely the fields of application to lower the chances that studies on the production and maintenance of devices (for example, in the keyword group "apps") appear in the search results.

The Scopus database was used for keyword search limiting the search field to title, abstract, and list of keywords. Furthermore, the search was limited to studies that appeared in peer-reviewed conference proceedings or journals. The literature search was conducted in December 2021. The database search yielded 1095 initial papers, which were subject to several selection and refinement criteria. First, after screening the initial sample, several new terms were added to the search string utilizing the Boolean operator "NOT" to exclude some irrelevant papers. For instance, excluding terms like "marketing," "buyer," and "shopping" can help avoid irrelevant papers in the sample dealing with apps as commercial platforms. Articles featuring such terms as "clinic*," "exercise," and "*therap*" usually focused on the application of mobile apps in clinical or rehabilitation environments and were, thus, also excluded. As a result, the sample size was reduced to 655 articles. In the next step, the remaining articles were evaluated to exclude ones that do not focus on app-supported human-centric production and logistics management. The title, abstract, and keywords of the articles were screened, and the following criteria were applied. 1) The articles must have an industrial setting. Hence, apps for smart homes, agriculture, or clinical use were considered irrelevant. 2) Apps are used to support human operators in industrial work. Thus, studies focused on the manufacturing of smart devices, apps' interface design, or smartphone user behavior were excluded. After this step, 74 articles remain in the working sample.

Finally, the remaining articles were read and classified according to the four-stage model of automation proposed by Parasuraman et al. (2000). The four stages are 1) information acquisition, 2) information analysis, 3) decision and action selection, and 4) action implementation. For each article, whether human operators are supported by mobile apps in each step mentioned above was evaluated. The articles remaining in the final sample had to cover at least three of the four stages, and at least two of the three stages had to be mainly supported by mobile apps. In addition, the studies should reach the technology-readiness level 4 according to Mankins (1995), that is, the proposed solution should at least have been validated in a laboratory environment, and details of the experimental evaluation should have been provided in the published research. These criteria were used to exclude preliminary, technology-focused studies and to focus on more advanced studies showing the potential of mobile apps in industrial applications. Two examples of the articles excluded in the final step are described here. Yang et al. (2017) developed an iPhone application to measure upper arm elevation and angular velocity for occupational risk analysis. By utilizing the embedded inertial motion unit of smartphones, the app supports human operators in information acquisition because it captures their body postures and movements. In addition, built-in algorithms make information analysis possible. However, the functionality of the app was not extended to the third and fourth stages. Thus, the app supports neither decision and action selection (e.g., warning function or action recommendation) nor action implementation (e.g., controlling tools, such as robots, to reduce human workload); therefore, this work was excluded from the final sample. Another example is a study conducted by Woll et al. (2011), in which an app was employed in a serious game for teaching in the assembly process. The app was evaluated by the user, but without a statistically validated study. The study was thus considered to be a "proof-of-concept" approach (technology readiness level 3), and the article was removed from the sample. This filter reduced the sample size to 14. Ten additional articles were identified during a snowball search.

3. RESULTS

The 24 sampled papers are classified into six categories based on their main supporting technologies (listed in descending order according to the number of papers in "Papers related to topic"). Here, we shortly define the application of these technologies in context of our sample papers.

1) *AR/VR (Augmented/virtual reality):* Augmenting the real-world situation captured by camera with extra information on devices' screen (AR); or creating a virtual 3D view of the real-world situation for remote experts.

2) *Image recognition:* Identifying images captured by devices' cameras.

3) *Motion capture:* Capturing motions of operators (e.g., hand gesture) or robots (e.g., trajectory)

4) *Vital data measurement:* Capturing operators' vital sign (e.g., heart rate) during work.

5) *Indoor positioning:* detecting location information of operators or machines inside factories or warehouses.

6) *Audio recognition:* Identifying operators' voice command or sound generated by operating machines.

There might be overlaps between the categories. For example, in category 1, image recognition is also used to identify objects, on whose basis the augmentation can be presented to the operators. Visual augmentation can be controlled by operator voice or gesture commands, with the help of audio recognition and motion capture, depending on the device capabilities. As both image recognition and voice/gesture commands support the AR system, AR is considered the main enabler in these studies.

Figure 1 shows the results of the classification, in which "Papers related to topic" refer to the 74 papers before the selection based on the four-stage model of automation was applied (see section 2). Owing to space restrictions, a strict selection procedure, as outlined in Section 2, was applied. Therefore, the articles in categories 4 are not discussed. One example of studies in this category is briefly presented. As also stated by Demrozi et al. (2020), vital data, such as heart rate, can be measured by smartwatches (e.g., Papoutsakis et al., 2021). However, the studies in this field, within our initial sample, were all conducted as an experimental approach. Hence, most focused on how vital data can be measured in industrial processes and the accuracy of the measurement ("information acquisition"). Support in the steps "decision and action selection" and "action implementation" can, in most cases, hardly be detected. In addition, some works in this category address the possibility of utilizing vital data to support decision and action selection (e.g., workers' break management in Kretschmer et al., 2021), but appropriate validation experiments were not conducted.

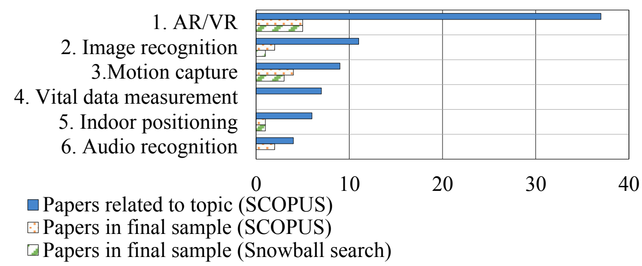

Figure 1. Classification of the sampled papers based on their main enablers

A more comprehensive overview of the abilities of apps and smart devices in vital data measurement can be found in the work of Pateraki et al. (2020). In the following, the remaining five categories of the final sample are discussed. The objective is to describe the apps' support based on their enabling technologies.

3.1 Augmented and virtual reality

AR/VR, contributing the most articles to the final sample, can realize a monitoring and controlling function in production and logistics. Apps can be developed on smartphones or tablets to augment such information as machine states and production parameters on the screen of devices (Subakti and Jiang, 2018). When smart devices are coupled with a camera on robots (Hashimoto et al., 2011) or forklifts (Correa et al., 2010), operators can utilize the information provided by AR to control them remotely. Another application of AR/VR that mobile apps make possible is the maintenance process. With the help of computer-aided design models projected on images captured by smart device cameras, machine defects can easily be detected. Ben Abdallah et al. (2019), for example, integrated AR in a tablet application to support aeronautical mechanical assemblies. The resulting system can detect errors in assembly and defects during maintenance. Defect detection can only identify parts that are missing or poorly mounted in this case. Mourtzis et al. (2021) combined AR with machine monitoring and (re)scheduling, so that the developed app makes online maintenance possible. Despite retrieving information from the system, AR apps also facilitate information exchange between operators. For example, Flatt et al. (2015) proposed a tablet application that enables operators to place virtual "sticky notes" on production modules. The system provides not only static maintenance information but also dynamic and recurring maintenance tasks from other operators, so that the application provides "context-aware" assistance. Another research stream describes the AR/VR application in telemaintenance, in which real-life situations are captured by the camera of the mechanics and transferred to the VR system of the experts. They create instructions, which are shown on the tablet AR application of the mechanics (Kleiber and Alexander, 2011; Kleiber et al., 2012). AR/VR mainly supports human operators in information acquisition and decision making. The information acquisition procedure is performed by the built-in camera of the smart devices, and the decision-making procedure is supported by static or dynamic information provided by the AR system. By utilizing this information, human operators can perform or learn tasks more efficiently (e.g., Mourtzis et al., 2021). In addition, information for occupational safety (e.g., when to turn off a machine during maintenance) can be integrated into the app (Tatić and Tešić, 2017).

3.2 Motion capture

Motion capture makes it possible for human operators and the system to interact. Villani et al. (2016) utilized the gesture recognition capability of smartwatches to interact with a troubleshooting system by controlling the instructions shown on the screen. Villani et al. (2020) proposed a smartwatch-supported system in which wrist movements and gestures are captured to control robots remotely. Hossain et al. (2017) applied smartphones to identify the trajectory of a robot arm. This application supports human operators in teaching robots collaborative assembly tasks. In addition, motion-capturing apps can improve the performance and safety of working systems. For instance, such accidents as falls (Casilari and Oviedo-Jiménez, 2015; Fang and Dzeng, 2017) can be detected. The detection can be utilized to activate emergency phone calls and improve process safety. By combining sound and acceleration data captured by smartphones, Kudo et al. (2020) managed to identify whether maintenance workers forgot to close the server rack doors, which is a risk to operator and facility safety. Regarding system performance in warehousing, Grzeszick et al. (2016) used a smartphone and smartwatch to recognize the picking action and to check whether the correct pick was made by automatically scanning the picked item through the cameras of the smartphone if the picking action was recognized. To sum up, the results show two main patterns of app support for motion capture. First, accelerometers embedded in smart devices are utilized to detect or identify operator or robot motions. The captured motion can then support either decision making (e.g., detecting incorrect picks (Grzeszick et al., 2016) or action implementation (e.g., controlling robots, Villani et al., 2020; Hashimoto et al., 2011).

3.3 Indoor positioning

Despite a large number of studies on indoor positioning in the initial sample, only two were included in the final sample. The reason was that most studies concentrated on the evaluation of system accuracy, and the application of this technology through mobile apps in the industry could hardly be detected. The two articles in the sample deal with tracking operator locations in industrial environments. Khadonova et al. (2020) developed an app that makes remote task assignment possible according to the operator location and provides automatic notifications when operators enter a prohibited or dangerous zone. Depari et al. (2018) utilized the positions of operators for evacuation management (e.g., planning paths and notifying rescuers when workers are in trouble).

3.4 Image and audio recognition

Owing to the similarity of support from image and audio recognition, both functions are included in this section. First, image recognition supports information acquisition. As stated by Li et al. (2021), smartphone apps can identify QR codes and handwritten labels. Ueda et al. (2020) applied image recognition in meter reading, given that replacing traditional monitoring meters with digital ones is expensive. Minnetti et al. (2020) utilized smartphone cameras to measure the gap and flush in car assembly lines for quality control. Similarly, audio recognition can be applied to inspect machines and ease the workload of maintenance staff. Verma et al. (2013) employed a smartphone microphone to record the sound generated by machines, which makes automatic fault diagnosis possible. Moreover, audio recognition can be applied to audio commands to control robot (Gkournelos et al., 2018) or vehicle (Correa et al., 2010; Saod et al., 2016) movements.

4. HUMAN-CENTRIC ANALYSIS OF SUPPORTING FUNCTIONS

In the previous section, the sampled papers were discussed based on the main enabling technologies. In this section, how mobile apps can support human factors is discussed to make a human-centric analysis possible. The app-supported tasks are categorized into perceptual/mental, physical, and psychosocial aspects during manual industrial work. As shown in Table 2, by utilizing the components of smart devices, human perceptual/mental, physical, and psychosocial aspects during work can be supported.

Table 2. Human-centric analysis of supporting functions

Category	Main enabling component(s)	Supported tasks
Perceptual/ Mental	Camera	Monitoring machine state (1) Monitoring operational environment (1) Detecting assembly fault (1) Identifying machine for maintenance (3) Reading code/label/meter (4) Inspecting surface (4)
	Screen	Transferring information/knowledge (1)
	Accelerometer	Teaching robot's trajectory (2)
		Controlling instruction system (2)
	Microphone	Detecting machine failure (5)
Physical	Screen	Providing safety information (1)
	Accelerometer	Controlling machine/robot (2) Detecting fall (portent) (2)
	Accelerometer & Microphone	Detecting safety hazard (door left open) (2)(5)
	Accelerometer & Camera	Ensuring process accuracy (wrong pick) (2)(4)
	Beacon	Assigning tasks remotely (3) Warning safety hazard (3) Planning emergency evacuation (3)
	Microphone	Controlling machine/robot (5)
Psychosocial	Heart rate sensor	Adaptive task assignment (6)
Enabling technologies: (1) AR/VR (2) Motion capture (3) Indoor positioning (4) Image recognition (5) Audio recognition (6) Vital data measurement		

Most works focused on perceptual/mental and physical aspects, whereas psychosocial aspects were only discussed in one work. Villani et al. (2020) proposed an adaptive interaction system in which smartwatches make remote control possible through operator gestures (motion capture). Additionally, the heart rate variability of operators is measured to estimate mental fatigue. Robots take over more tasks if stress is detected, so that the human–robot interaction is simplified, and the capabilities of humans and robots are combined to achieve a better system performance. Therefore, a research gap in app-supported psychosocial aspects can be identified. As stated by Neumann et al. (2021), people have psychosocial needs. Ignoring these needs can lead to mental illness and physical disorders. The example mentioned above shows the possibility of app support in this area. Further studies should also use apps to support teamwork, motivation, among others, to contribute to the development of sociotechnical systems in the industrial domain.

5. CONCLUSIONS

Preliminary results of a systematic literature review on app-supported human-centric production and logistics management were presented, and potential applications of commercial smart devices in industrial settings were outlined. By applying the four-stage model of automation during the selection of articles and categorizing them according to different human factors, it was possible to outline the opportunities to integrate mobile apps and their enabling technologies/components to support human operators in industrial processes. AR/VR, motion capturing, indoor positioning, and image and audio recognition were identified as important enabling technologies for mobile apps. It can be concluded that most ready-to-use applications focus on perceptual/mental and physical support. The psychosocial aspects of app usage require more research attention.

This study has limitations that must be addressed in future work. First, the literature search should be extended, and more databases should be used to find more relevant research. Second, by applying strict selection rules, some studies (e.g., those without validation) in which insights can be gained for future applications were not included and discussed in this review. An extension of this work should have a broader focus to gain more insights. Third, the articles should be evaluated in more detail with regard to validation experiments to determine the limitations of mobile apps and smart devices (e.g., smartphone AR systems vs. AR glasses), ethical considerations of app usage in daily work, and operator acceptance of these systems.

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