Sitting Posture Recognition and Feedback: A Literature Review

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ABSTRACT

Extensive sitting is unhealthy; thus, countermeasures are needed to react to the ongoing trend toward more prolonged sitting. A variety of studies and guidelines have long addressed the question of how we can improve our sitting habits. Nevertheless, sitting time is still increasing. Here, smart devices can provide a general overview of sitting habits for more nuanced feedback on the user's sitting posture. Based on a literature review (N=223), including publications from engineering, computer science, medical sciences, electronics, and more, our work guides developers of posture systems. There is a large variety of approaches, with pressure-sensing hardware and visual feedback being the most prominent. We found factors like environment, cost, privacy concerns, portability, and accuracy important for deciding hardware and feedback types. Further, one should consider the user's capabilities, preferences, and tasks. Regarding user studies for sitting posture feedback, there is a need for better comparability and for investigating long-term effects.

CCS CONCEPTS

• **Human-centered computing** → **HCI theory, concepts and models**; **Ubiquitous computing**; • **Hardware** → *Sensor devices and platforms.*

KEYWORDS

Literature review, posture, sitting, chair

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1 INTRODUCTION

We sit for a large part of the day, for example, while working, riding the bus, watching television, or browsing social media. Sitting and the more often studied sedentary behavior — a broader term including sitting, reclining, and lying postures with low energy expenditure [230] — negatively affect our health [42, 178, 211]. Thus, there is a concern about the development of more sitting-focused lifestyles. Prior work already addresses this issue by proposing various methods to reduce it, breaking it up with physical activity, e.g., [50, 98, 100, 210], or standing up [25, 72, 87, 163]. These countermeasures are not always possible, or only to some extent, depending on the person's abilities, task, and environment. Lam et al. [114] investigated the option of reduced sedentary behavior. They found that interventions targeting the physical environment, such as sit-stand desks [218] or novel furniture [41, 182], reduce sedentary behavior most effectively, followed by interventions targeting personal behavior, like consultations or apps. Today's guidelines [153] suggest an upright posture, commonly viewed as healthier [5, 106, 113, 217, 246]. However, recent research suggests that the importance lies in the frequent change of sitting postures [24, 243] reflected in the guideline by the National Library of Medicine [153].

Supporting people to sit healthier through a smart system thus requires the ability to recognize their sitting posture and communicate the necessity of posture change through feedback. A large body of prior work addressed these challenges by proposing computer-supported recognition of postures and guidance for better poses. There have also been reviews about sitting posture recognition [97, 160, 229]. Tlili et al. [229] found and compared techniques using weight, tilt angle, spine curvature, and combinations of multiple sensor types to get information about a user's posture. They provide an extensive table of publications with details, such as the type and number of sensors and the used communication technology. Kappattanavar et al. [97] systematically reviewed hardware and classification methods for sitting posture recognition. They found pressure sensors and neural networks to be the most prevalent sensor types and classification methods. The authors suggest using Inertial Measurement Units (IMUs) for classification and 3D cameras to gather ground truth data and further propose five basic sitting postures due to the lack of a standard definition. Most recently, Ordean et al. [160] conducted an Analytic Hierarchy Process (AHP) analysis comparing six types of posture detection (e.g., visual

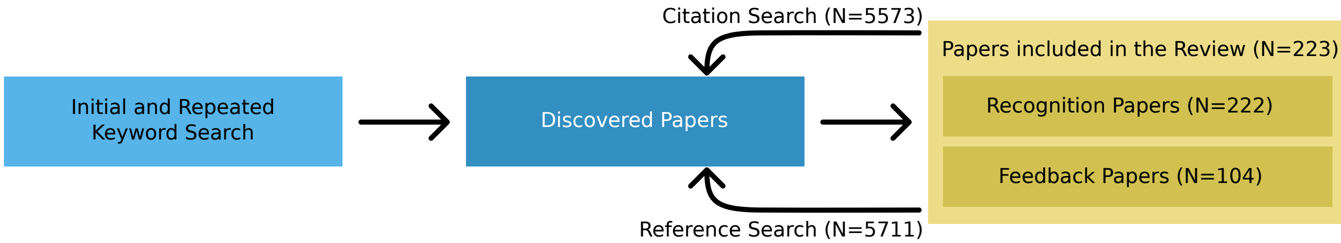


Figure 1: A diagram of the process of the presented literature review. For each publication included in the review, we screened references and citations for new papers to include. For all works found this way, we subsequently performed the same search.

inspection systems) based on seven criteria, such as accuracy and privacy. They conclude that the ideal solution is finding the user's mass center and upper-body tilt. Giving feedback about posture has also been studied extensively, exploring various modalities such as vibration, sound, visualizations, and hardware that actively corrects the user's posture. However, we are unaware of a review of this body of work.

We contribute a broad literature review of sitting posture recognition and feedback, which we hope will guide future research in computer-supported sitting guidance. Our work expands previous reviews about recognition by a larger number of included publications. Further, our review is, to the best of our knowledge, the first review of feedback for sitting posture. In detail, we conducted a seed-paper-driven literature review covering sitting posture recognition hardware and feedback. Upon identifying a publication as relevant for our review, we searched through its citations and references to find further relevant papers. We found 223 papers that addressed these challenges in their publications. We categorize the publications and showcase them in both textual and tabular form. The papers we found cover a wide range of research areas, like computer science, human-computer interaction, health, engineering, sensors, bioengineering, and more, see Figure 2. The widespread attention given to recognizing and providing feedback on sitting posture emphasizes the need for a broad overview incorporating knowledge from various research fields.

Our literature review uncovered a large body of work addressing how posture can be captured and how feedback should be communicated. We found a large variety of methods and combinations thereof being explored for both. Pressure sensors are the most commonly used hardware, and visual is the most common feedback modality with many techniques such as charts, sketches, physical objects, and more. We concluded that the most suitable hardware depends on the use case, cost, privacy concerns, portability, and accuracy. Many publications report high accuracies for automatically classifying postures. We refer to [97, 229] for reviews of this aspect. We found a large body of work exploring feedback about sitting postures, suggesting advantages for all feedback modalities and various types of visual feedback. We argue that all modalities and types have advantages, depending on the environment and the users' abilities, circumstances, and preferences. The 64 user studies of sitting posture feedback we examined showed a generally positive reception by users and a positive influence on their sitting behavior. We also found, however, the need for long-term studies and more comparability between approaches and suggest open questions we see toward this goal. In sum, the main contribution of this work is the overview of sitting posture recognition and feedback, revealing possible directions for future work on improving people's health while sitting.

2 METHOD

We conducted a seed-paper-driven literature review; see Figure 1 for a diagram of our approach. Upon identifying a publication as relevant for our review, we searched through its citations and references to find further relevant papers. This resulted in 223 publications about sitting posture recognition (222) and feedback (104), published between 1968 and 2022. The distribution of the papers over time can be seen in Figure 2. This reveals a gap of over 20 years after the first works in the seventies and yearly publications only after 2005. As a first step, we performed a manual keyword search in the online databases Google Scholar[1] and Connected Papers[2]. The keywords we searched for were "sitting healthy", "sitting posture", "sitting time", "prevalence of sitting", "sitting posture recognition", "smart chair", and "sitting posture feedback". This initial search resulted in a small collection of seed publications about sitting, sitting posture recognition, and sitting posture feedback [9, 63, 74, 107, 134, 157, 175, 189, 236, 245]. The same searches were conducted again a few times over three months, as suggested by Rogers and Seaborn [183]. For every relevant publication added to our review, we searched through its citations and references to find further relevant papers. This process resulted in 11284 scanned papers. We repeated this process for all relevant papers until we could not find any additional papers relevant to sitting posture recognition and feedback. Further, we checked whether the most recent publications were cited by newly published work. The last check was done in November of 2022. To guarantee a clean sampling process, we re-examined all included publications after the completed analysis with the sharpened definitions and understanding that has evolved. This resulted in three papers being removed from the feedback part of the review and one that was excluded completely.

We had several exclusion criteria to keep our review focused and manageable. First of all, we excluded papers investigating non-sitting postures such as general body posture, hand posture, or posture while running, e.g., Liao et al. [125]. Although related, we want to provide a more focused overview of postures related to sitting. Second, we also excluded papers about posture analysis

[1] https://scholar.google.com/
[2] https://www.connectedpapers.com/

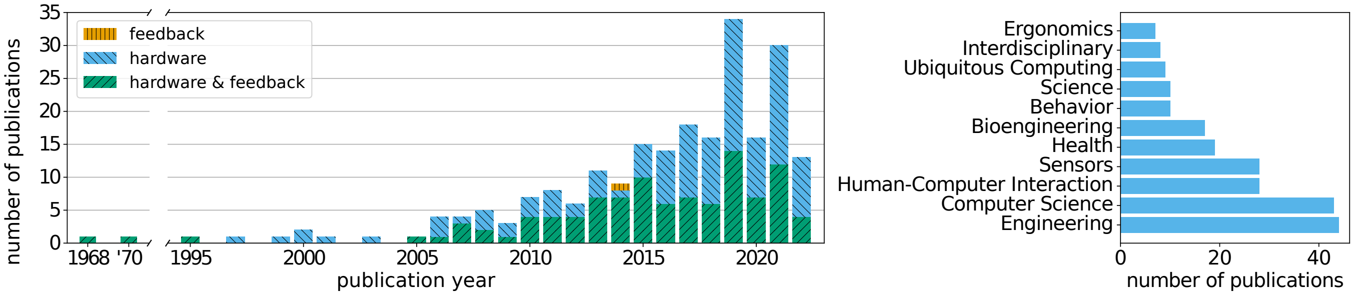


Figure 2: Overview of the publications in the review. The distribution of sitting posture recognition and feedback papers over the years (left) and the research areas represented in the review (right). The colors are based on the work by Wong [247].

methods such as RULA [141], used to investigate ergonomics of workplaces, and SEAT [168], which is concerned with injury risk while interacting with software. Third, publications presenting systems that measured humans' sitting behavior for other reasons than determining sitting posture were also not included, e.g., Iskandar et al. [86]. Further, we excluded papers that did not focus on sitting posture but on sitting time. Examples are approaches to breaking sitting time up or reducing it [9, 18, 43, 87, 177, 213]. Although the goals are similar from a health perspective, the data is different (i.e., sitting postures do not have to be differentiated), and with smart devices, widespread commercial solutions already exist. Nevertheless, providing such feedback is important, and there is still room for improvement. We want to highlight one publication by Jafarinaimi et al. [87] that, although only using sitting time, created visual feedback through a physical object that would also be suitable for sitting posture recognition. Finally, we excluded publications that did not provide enough details about their feedback to allow comparison with other approaches.

The discovered papers were clustered by the topics SITTING, POSTURES, PRESSURE SENSORS, OTHER HARDWARE, ACTIVELY CHANGING THE USER'S POSTURE, SITTING POSTURE FEEDBACK, FEEDBACK FOR DIFFERENT POSTURES, and META/ REVIEW. To cluster, we first read the abstract and then, if necessary, the entire publication. We used a web-based whiteboard tool[3] to display the papers and their connections colored according to their categorization. We decided not to use a database query approach for two main reasons: The various terms used to describe sitting posture recognition and the spread of the topic over many research areas (see Figure 2). The variety of used terms can be shown with a small example. If we only consider the eleven papers in our review whose title start with "posture", there are seven different words we find synonymous with "recognition" for this work: detection, estimation, monitoring, prediction, sensing, tracking, and training. Words such as "sitting" or "sedentary" only appear in the titles and keywords of three of these papers. However, the only keyword not mentioning sitting, namely "smart chair", would only discover two of the eleven papers. This variety of terms makes it challenging to find publications about this topic using only keywords. Because of the many research areas that cover sitting posture, a database query approach might inadvertently exclude publications, especially when limiting which databases are being searched. Thus, we chose to take a "multi-part contribution" [212] approach. Stefanidi et al. [212] argue that such an approach "allows for addressing a wide variety of different aspects without going beyond the standard publication length," which aligns with our goal to provide a broad overview of the topic at large. While our review might not be exhaustive, we believe it to provide a representative overview of the research on sitting posture recognition and feedback.

[3]https://miro.com

Please refer to the supplemental material for a list of all reviewed publications, the data and code for the presented and additional charts, and detailed recognition, feedback, and user studies tables.

3 SITTING POSTURE RECOGNITION

There is a plethora of work exploring technologies with which sitting posture can be detected (222/223). Although pressure sensors are the most prevalent (97/222), the most fitting solution depends on the specific use case. In order to avoid disturbing someone with too many notifications while reminding them to change their sitting posture and take breaks, it is vital to understand how they are sitting and for how long. Manually scoring sitting postures [201, 202] or giving in-person training [45] is not feasible on a larger scale because of the required time and human resources. Hardware and automation are required to detect and differentiate between sitting postures to make sitting posture recognition and feedback scalable.

While many papers report high accuracy, comparing this aspect is outside the scope of this work and, we believe, will prove to be a difficult task, as many fundamental aspects of these systems are very heterogeneous. Defined postures range from binary good and bad (e.g., [227]) to 30 individual postures [46]. Classifications range from comparing sensor values to thresholds (e.g., [117]) to various machine learning approaches (e.g., [126, 236]). For an extensive review of sitting posture monitoring systems and different classification approaches, we refer the reader to the reviews by Tlili et al. [229] and Kappattanavar et al. [97].

This extensive research area overview covers the hardware used in 222 papers. We categorized them based on the type of measurements used to recognize sitting postures into pressure sensors, motion sensors, vision-based setups, distance sensors, deformation sensors, and combinations. We put setups that we could not cluster any further into the category *other*. The intersection between recognition and feedback approaches can be found in Table 1, and a detailed view of the hardware can be found in the supplementary material.

Table 1: Combinations of hardware and feedback approaches of the papers in our literature review. The feedback modalities are ACTIVE (AC), AURAL (AU), VIBROTACTILE (VIB), and VISUAL (VIS). Publications not featuring feedback or not using hardware fall under NOT APPLICABLE (N/A). Note that publications featuring more than one feedback modality appear in multiple rows.

Hardware × Feedback	**AC** (14)	**AU** (32)	**VIB** (33)	**VIS** (69)	**N/A** (119)
Pressure Sensors (97)	(5) [63, 137, 154, 167, 196]	(5) [7, 40, 140, 149, 206]	(12) [7, 28, 67, 70, 81, 82, 129, 175, 186, 206, 232, 262]	(21) [6, 7, 40, 67, 70, 115, 131, 140, 143, 148, 164, 172, 179, 186, 196, 209, 224, 232, 240, 241, 255]	(64) [1–3, 9, 14, 16, 21–23, 29, 30, 32, 35, 39, 55, 59, 61, 62, 65, 66, 71, 76, 77, 79, 80, 83, 88, 95, 103, 104, 110, 122, 126, 130, 133, 136, 138, 139, 142, 152, 169, 176, 177, 184, 185, 189, 193–195, 204, 205, 216, 220–222, 226, 236–238, 254, 256, 260, 265, 266]
Motion Sensors (36)	(1) [105]	(10) [27, 31, 105, 123, 124, 159, 180, 227, 239, 251]	(10) [27, 94, 111, 112, 123, 124, 170, 171, 198, 239]	(12) [27, 31, 74, 105, 123, 124, 156, 159, 170, 198, 227, 239]	(18) [54, 68, 69, 96, 108, 127, 134, 145, 161, 166, 181, 187, 192, 203, 223, 228, 234, 248]
Vision-based (31)	(4) [13, 85, 200, 253]	(5) [36, 64, 150, 162, 214]	(1) [85]	(12) [15, 47, 58, 64, 85, 89, 102, 150, 162, 225, 242, 245]	(14) [34, 38, 46, 73, 90, 107, 128, 135, 144, 208, 215, 250, 252, 257]
Distance Sensors (9)	(1) [199]	(3) [4, 116, 155]	(1) [116]	(1) [4]	(5) [19, 56, 57, 99, 119]
Deformation Sensors (8)			(2) [17, 157]	(2) [44, 157]	(5) [8, 48, 49, 93, 173]
Other (17)	(2) [197, 231]	(4) [11, 45, 52, 258]	(2) [52, 158]	(10) [45, 60, 165, 201, 202, 207, 219, 231, 259]	(2) [190, 233]
Combi-nations (25)	(1) [117]	(5) [75, 120, 174, 249, 267]	(5) [109, 117, 263, 264, 267]	(12) [12, 37, 51, 75, 84, 109, 117, 118, 151, 174, 263, 267]	(10) [10, 20, 53, 78, 92, 121, 132, 188, 191, 261]
N/A (1)				(1) [101]	

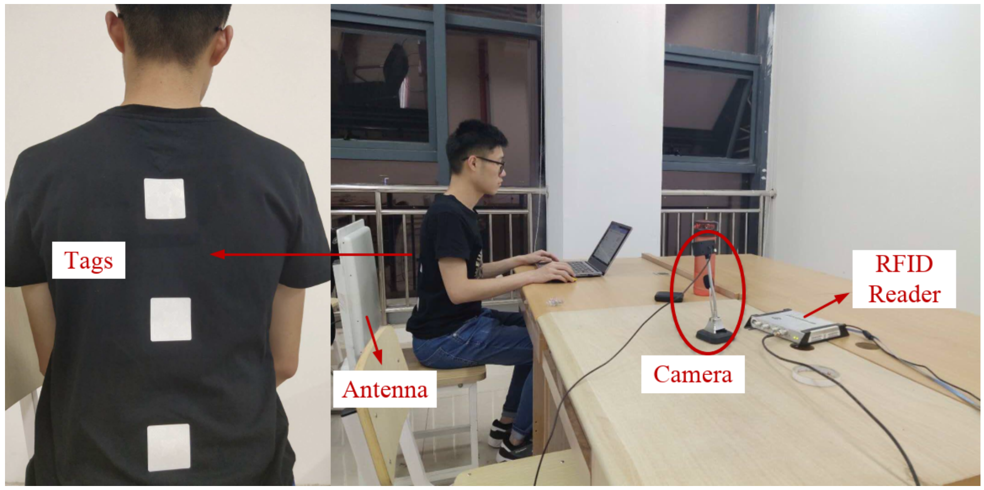
3.1 Pressure Sensors

Pressure sensors are the most commonly used hardware in the literature to detect sitting posture (97/222). While we found one instance where a pressure sensor was worn [204], they were generally attached to a chair. The term *pressure sensor* is rather broad, including sensors of various forms and functions. The most common (85/97) are pressure sensors that are thin and flexible and can be sat on directly without the user noticing. They use materials that change voltage or resistance when mechanical pressure, force, or stress is applied, for example, through their piezoelectric, piezocapacitive, or piezoresistive properties. There are many variants, such as flex sensors, textile pressure sensors, and Force Sensitive Resistors (FSRs), which we summarized as Thin and Flexible Pressure Sensor (TFPS). They can be placed anywhere without being noticed by the user and have thus been used the most for sitting posture recognition. The form of these sensors varies, ranging from larger ones that cover the entire seat of a chair to smaller ones that are distributed sparsely over its surface. They can be placed on top, below, or inside of cushioning. Typical placement options in research were on a chair's seat (e.g., [95, 115]), backrest (e.g., [29, 110]), or both (e.g., [95, 115]). They can also be integrated into a portable pad that does not bind the setup to a specific chair [29, 81, 82, 110]. In one case, sensors were placed on the seat, backrest, and the chair's armrests [30]. Cheng et al. [35] followed a different approach by placing pressure sensors below a chair's legs.

Other pressure sensing methods include sensors that measure the air pressure inside bladders on which the user sits (e.g., [137, 138]) and a device that bends an optical fiber when someone sits on it [224]. The applied pressure can then be measured through the effects on the transmitted light. Others used load cells [23, 184, 185] and force transducers [70, 194, 195]. These sensors use rigid metal bodies that deform through applied forces such as pressure. This deformation is then measured through an electronic component, such as a strain gauge. They are placed beneath a plate or board for sitting posture detection, as they would be uncomfortable to sit on. Some put such sensors between the seat and the base of a chair (e.g., [194, 195]), while Roh et al. [184] put them below a removable cushion, and Bibbo et al. [23] placed load cells in 3D-printed enclosures and customized the frame of a chair to attach them.

The placement of pressure sensors on a chair's seat is the most promising approach, whereas sensors on the backrest offer supplementary data but require user contact. Pressure sensors are affordable (costing less than 10 USD) and readily available, with comprehensive software integration support. They operate independently of various users, rooms, or tables, ensuring comfort; however, most implementations presented in the literature cannot be easily attached to different chairs. Furthermore, they face challenges in their assembly process due to their limited coverage of the user's contact area, which means they only utilize a fraction of the user's body weight to determine their posture. Larger sensor matrices can mitigate this effect but come with increased cost.

(a) *Hong et al [74], ©ACM 2015*



(b) *Feng et al. [56], ©IEEE 2019*

Figure 3: Examples of motion and distance sensors for sitting posture recognition: (a) a gyroscope attached to the upper back and RFID tags on the lower, middle, and (b) upper back with the corresponding antenna attached to the backrest of a chair.

3.2 Motion Sensors

Sensors that measure movement are the second most common (36/222) technology to recognize sitting posture in the literature. They include accelerometers (e.g., [111, 248]), Inertial Measurement Units (IMUs) (e.g., [227, 239]), gyroscopes [54, 74, 234], linear displacement sensors [108, 166], and angular displacement sensors [112]. They were usually worn (see, for example, Figure 3a), but Otoda et al. [161] and Mizumoto et al. [145] attached them to a chair. Worn approaches are chair-independent; they allow users to switch chairs and detect sitting posture regardless of the object they are sitting on. Unlike pressure sensors, motion sensors do not require direct contact with the chair, such as the backrest, enabling pose evaluation without touching the chair's surface. Furthermore, they are affordable (under 5 USD), commercially available, compact, and less sensitive to placement position than pressure sensors. However, wearing them might cause discomfort to the user and require a more complicated calibration process than pressure sensors.

3.3 Vision-Based

We found vision-based setups, such as those using a Microsoft Kinect (e.g., [47, 252]), to be the third most commonly used technology (31/222) for recognizing sitting posture. Others opted for cameras with various recognition approaches, such as face detection (e.g., [150, 242]), silhouette extraction [89, 90, 135], the use of OpenPose [34, 250], motion capturing [64], and deep learning [107]. Vision-based approaches are chair-independent, providing maximum comfort with a setup placed next to the user. The setup is more straightforward than other approaches and can track arm positions. However, vision-based approaches entail using cameras, which are pricier than alternative solutions. Privacy and confidentiality concerns may also arise, and comparatively high computational demands are associated with this method.

3.4 Distance Sensors

Recognizing posture through distances has been done (9/222) with Radio-Frequency Identification (RFID) tags [56, 57, 119] (see, for example, Figure 3b), ultrasonic sensors [4, 155], depth sensors [19, 116], Lidar [99], and HTC VIVE Pro trackers [199]. These distance-measuring sensors can either be worn or placed stationary. This flexibility allows users to choose their preferred trade-off between comfort and the option to use the same sensors in different environments. Ultrasonic and depth sensors are cost-effective (under 15 USD) and readily available commercially. Lidar sensors can be used over greater distances but are more expensive and larger than the other options. Unlike vision-based approaches, distance sensors pose fewer confidentiality and privacy concerns, and processing their signals is less computationally demanding.

3.5 Deformation Sensors

We found seven (7/222) publications that determined sitting posture through sensors that measure deformation, such as bending or strain. These included flex sensors [8, 44, 157], strain sensors [17, 173], optical fiber sensors [48, 49], and a charge-generating fabric [93]. Deformation sensors are easy to find commercially and come at an affordable price (under 10 USD). They are usually worn on the user's clothing or skin and offer similar benefits to other types of wearable sensors. However, certain concerns need to be addressed when it comes to deformation sensors. For instance, issues may arise if individuals of varying sizes use the same clothes with attached sensors. Moreover, proper calibration is necessary, and comfort-related problems can also occur.

3.6 Other

Other approaches (16/222) we found in the literature include the above-mentioned manual inspection (e.g., [45, 197]) and mechanical switches [11, 158, 231, 259]. There have been single examples of capacitive proximity sensors [60], an Electromyography (EMG) setup [165], an inductive proximity sensor [258], electrodes [233], and temperature sensors [190]. Except for the manual inspection approach, these techniques have advantages and disadvantages similar to the other recognition hardware types discussed above. However, manual inspection requires either the user themselves or other individuals to assess the user's pose, placing demands on the user's mental resources or requiring additional human resources.

3.7 Combination of Sensor Types

In total, 25 of the 222 papers featuring recognition explored various ways of combining different sensor types, such as accelerometers with gyroscopes [249, 267] or a camera [53]. In one publication, a tilt sensor was combined with ultrasonic sensors [174]; in another, temperature and sound sensors were used together [191]. The majority (20/25) of combinations included a pressure sensor, like El-Sayed et al. [51], who combined load cells with inclinometers. Thin and Flexible Pressure Sensors (TFPS) have been combined with ultrasonic sensors (e.g., [10, 37]), infrared sensors (e.g., [92, 264]), Microsoft Kinect [84, 151], IMUs [132, 261], optical fiber-based bend sensors [121], a camera [12], and with an accelerometer [78]. In three publications, more than two different types of sensors were combined. Kumar and Sridhar [109] used TFPS with temperature, blood pressure, and pulse sensors, while Hong et al. [75] detected posture with TFPS, gyroscope, accelerometer, and infrared sensors. Finally, Benocci et al. [20] used TFPS, accelerometer, magnetometer, altimeter, and temperature sensors. Combining different sensor types naturally brings the advantages and disadvantages of both approaches together. It can enhance a system's accuracy and the quantity and variety of collected information. However, it also increases usage, setup, and overall cost complexity. Section 5 further discusses the trade-off between simple and complex systems.

4 SITTING POSTURE FEEDBACK

As the previous section shows, a large body of research has been conducted on various technologies and techniques to detect and classify sitting postures. Giving users feedback about their posture has also been studied extensively. Of the 223 papers we found, 104 describe sitting posture feedback. Researchers explored hardware that actively adjusts itself to directly or indirectly correct the user's posture (14/104), as well as aural (32/104), vibrotactile (33/104), and visual (69/104) modalities. Visual feedback is the most prevalent and varied approach in the publications we found. However, according to the multiple resource theory by Wickens [244], non-visual modalities could be beneficial for scenarios where the user's main task is highly visual, such as most office work. This part of the review covers the 104 papers and their approaches to map the research on sitting posture feedback. A table of all feedback publications can be found in the supplementary material. The intersection between recognition and feedback is shown in Table 1.

4.1 Visual Feedback

Visual is the most prevalent (69/104) approach for sitting posture feedback in the literature, with a wide range of different types, like ambient lights, text, sketches, and charts. We identified two main categories of visual feedback for sitting posture: time of delivery (TIME) and TYPE. Regarding TIME, feedback is delivered in REAL-TIME or SUMMARIZED after a certain period. The different TYPES we found are TEXT MESSAGES, SKETCH-LIKE DEPICTIONS, CHARTS, IMAGES OR VIDEOS, PHYSICAL OBJECTS such as ambient lights, and OTHER types, such as gamification. The following is separated into SUMMARIZED feedback followed by REAL-TIME feedback. A table with details about the visual feedback of all publications can be found in the supplementary material.

4.1.1 Summarized Feedback. One type of visual approach we identified gives the user SUMMARIZED feedback about their sitting posture after a certain time. We found 24 of the 69 visual feedback papers used such an approach, with charts being the most used type (18/24). There are bar charts (e.g., [4, 27]), line charts (e.g., [109, 123, 156, 231]), area charts [231], and pie charts (e.g., [37, 60, 101], see also Figure 4a). Others used dial charts to show the time spent in different postures [7] (see Figure 4b) and the health-risk level of the user [162]. Some examples of these chart types can be found in Figure 4. Furthermore, heatmaps were used to visualize the pressure distribution [231, 240], with two cases using LEDs on a sketched chair that were attached to the side of the chair [67, 232], as shown in Figure 6a. Further, Bagalkot et al. [12] created a rounded star plot, shown in Figure 4c, where each axis represents a characteristic of the sitting posture, such as leaning left. They describe this as an "amoeba-like blob" with the goal of easy readability at a glance while riding a motorcycle.

TEXT MESSAGES (1) and SKETCH-LIKE DEPICTIONS (2) rarely have been used for summarized feedback. El-Sayed et al. [51] sent daily textual reports as emails to the user's doctor for review. Sketches have been used in the form of stick figures by Ribeiro et al. [179], which depict different sitting positions and how much sitting time the user spent sitting in them, while Yu et al. [259] used a sketch of a person sitting at a desk with circles at the sensor positions. Those circles were colored green if the respective sensor value was scored as being at risk during a specific time frame. Wang et al. [241] followed another approach and combined sketches with CHARTS by augmenting pie and bar charts with depictions of different postures. In three cases, physical objects were used for summarized feedback [67, 186, 232]. They all used LEDs on a sketched chair that was attached to the side of the chair. These LEDs could display the most dominant postures of the previous half-hour; see Figure 6a for one example.

Three publications used less common methods to give summarized feedback. One is Khurana et al. [101], who used gamification [26] in the form of badges that could be earned, such as "exercise your neck for 3 minutes", visible in Figure 5d. Further, Murata and Shibuya [151] used a posture score, i.e., the proportion of time spent in a good sitting posture in the last hour, and a ranking comparing user's scores. Finally, Min et al. [143] showed the user a cartoon dog they had to keep healthy by adjusting their sitting behavior. They used status bars to display various parameters. For instance, if the user leaned too much toward the right, a bar indicating the dog's saturation would decrease. If these bars decreased to a critical level, the dog blinked, rotated its head, or panted. As the user performed countermeasures, the dog's animation responded accordingly, and its status improved.

(a) *Courtesy of and © by Khurana et al. [101] 2014* **(b)** *Anwary et al. [7], ©IEEE 2020* **(c)** *©Bagalkot et al. [12] 2020*

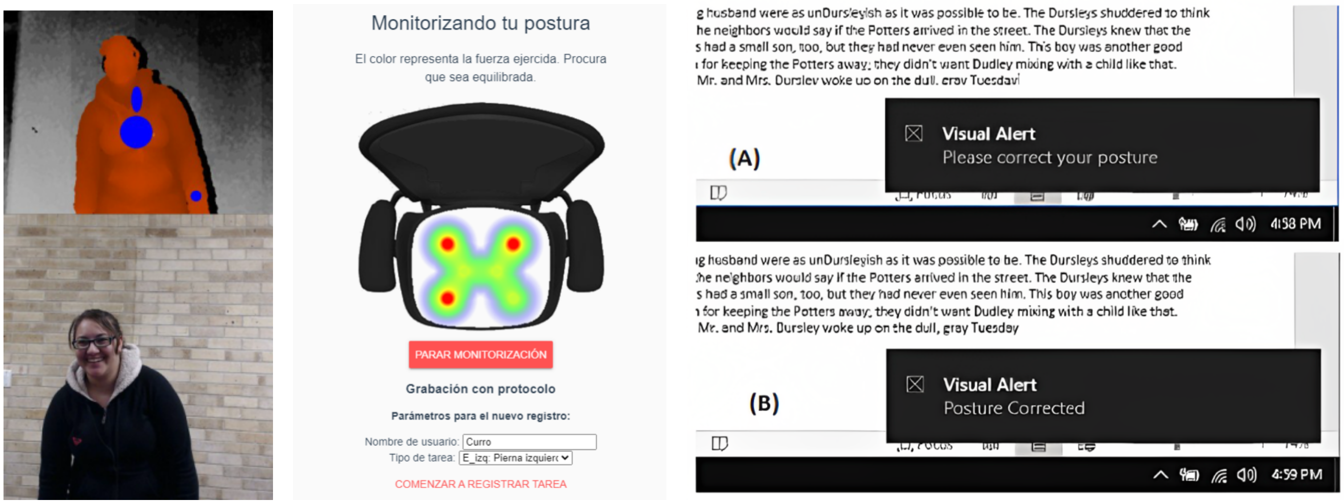
Figure 4: Examples of SUMMARIZED visual feedback showing information about the user's sitting posture through CHARTS: a bar chart showing time spent in different postures and a pie chart visualizing posture balance (a), a dial chart displaying time spent in different postures (b), and a rounded start plot visualizing multiple sitting posture parameters, like head and shoulder tilt (c).

4.1.2 Real-Time Feedback. The more common (66/69) type of visual feedback we found is given in REAL-TIME. A small subset of 8 publications used IMAGES AND VIDEOS to do so. For example, Taieb-Maimon et al. [219] showed the user a picture of their current sitting posture next to a previously taken reference picture after a fixed time. Sigurdsson and Austin [201] and Sigurdsson et al. [202] showed the users live video footage of themselves through which they had to score their posture. Another approach was followed by Taylor et al. [225], who used a large screen as a mirror, as shown in Figure 5a. The live video was then augmented by highlighting the parts of the user's body that deviated from good posture or, as a more general feedback, by displaying fog. TEXT MESSAGES have also been used to give real-time feedback (19/66), including prompts suggesting the user should change their posture, take a break, or exercise (e.g., [4, 105, 115, 209]); see Figure 5c for an example. More specific written suggestions on how to improve the current posture were also given (e.g., [27, 148]), as well as encouraging messages for sitting with a good posture [47].

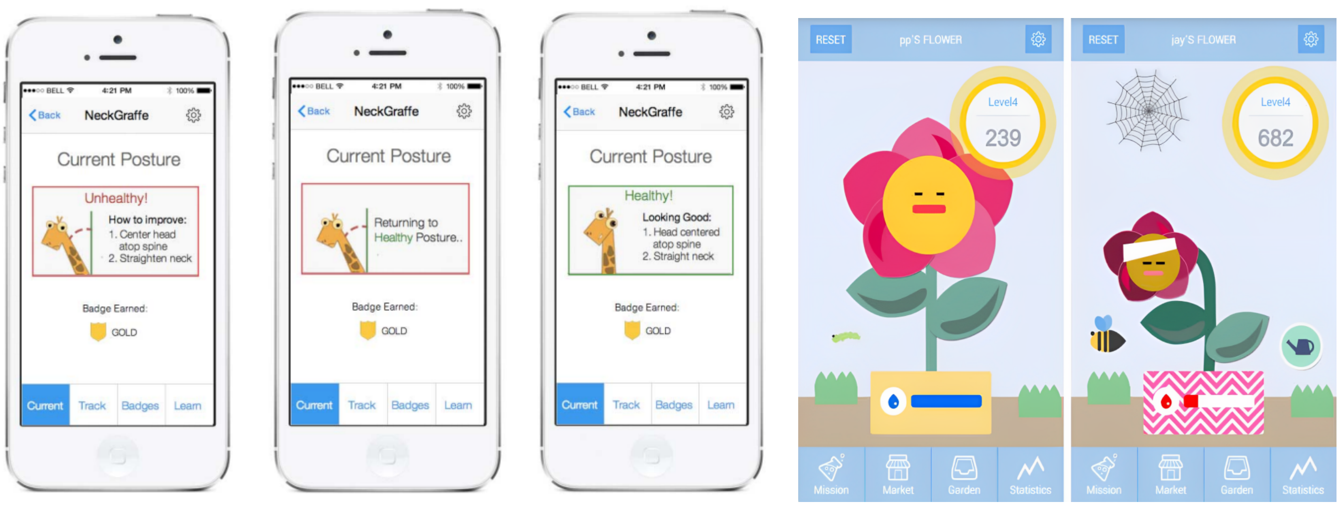
We found 20 publications that explored the use of CHARTS to give REAL-TIME feedback, including straightforward approaches such as bars being colored green or red depending on muscle activation [64, 165] or lines oriented according to the current angle of the user's lower and upper back [170]. Others used a line chart showing how much the shoulders are bent [227] and dial charts displaying the asymmetries of the current posture [6]. Jaimes [89] displayed a red and green bar over which a black bar moved, representing the user's left-right balance. Wang et al. [241] used a scatterplot with circles scaled according to the sensors' pressure values. Some publications feature heatmaps of the current pressure values [37, 255], with Wang and Yu [240] creating a three-dimensional heatmap in the form of a chair.

A total of 25 publications used SKETCH-LIKE DEPICTIONS to visualize their REAL-TIME sitting posture feedback. Kim et al. [102] displayed a turtle with a bent neck, referring to the "turtle-neck syndrome," which is how sitting with a forward bent neck is referred to in South Korea. Others used sketches of chairs with additional information, such as a color-changing background [172], pressure distribution percentages [7], or at-risk positions [259]. Demmans et al. [44] proposed a face icon that changes its expression based on the posture – it appears green and smiling when sitting upright and red and crying when slouching. In another article, Lee et al. [118] showed a human figure sitting upright or hunching to represent good and bad posture. Sketches of different postures have also been used, such as by Breen et al. [31], who showed the user their current posture and a red circle if it was considered unhealthy. Zheng and Morrell [263] used sketches to show cues for improving the current posture and sketches of a human's back and legs with colored circles where posture errors were detected. Further, Baptista et al. [15] explored a virtual skeleton to show the user their current posture and a suggested posture with arrows indicating the necessary movements to reach it.

Visual REAL-TIME feedback was also provided through PHYSICAL OBJECTS ranging from simple LEDs to complex objects that deform according to the user's posture. Of the 66 papers exploring REAL-TIME feedback, 16 used physical objects. One such technique is data physicalization, defined by Jansen et al. [91] as "a physical artifact whose geometry or material properties encode data." An early approach by Daian et al. [40] introduced a physical agent on the desk, which turned its back to the user if an inappropriate



(a) *Courtesy of and © by Taylor et al. [225] 2013* **(b)** *© CC BY Luna-Perejon et al. [131] 2021* **(c)** *©Kiran et al. [105] 2021*



(d) *Courtesy of and © by Khurana et al. [101] 2014* **(e)** *Hong et al. [74], ©ACM 2015*

Figure 5: Examples of REAL-TIME visual feedback: using IMAGES AND VIDEOS on a smart mirror where body parts that deviate from good posture are highlighted (a), a sketched chair with a heatmap of the pressure combining CHARTS with SKETCH-LIKE DEPICTIONS (b), utilizing TEXT MESSAGES through a desktop notification (c), an anthropomorphized giraffe with information and suggestions about the user's sitting posture (d), and an anthropomorphized flower enhanced through gamification (e).

posture was detected and moved from side to side to suggest a break. Hong et al. [75] created a physical flower, shown in Figure 6c, that can imitate the angle of the user's back while changing the color of its stem with LEDs from green to yellow as an analogy of poor health. Ferreira et al. [58] developed an origami structure that appears less symmetrical as the user's posture deteriorates. Another PHYSICAL OBJECT that has been used is ambient lights. Most approaches attach LEDs somewhere on the desk, which light up or blink to give feedback about improper posture [4, 67, 117, 162, 174, 186, 232]. Lee et al. [118] encased lights in an ambient display shaped like a cloud and moon and placed them next to the computer display. The two elements glowed dimly if the user sat in a low-risk posture and flashed red if in a high-risk posture. The physical flower of Hong et al. [75] also uses ambient lights, as described above. Others integrated LEDs into the clothes of the user. Özgül and Patlar Akbulut [267] attached an LED to a vest, while Nishida and Tsukada [156] sewed LEDs into the sleeves of a sweater and Soltani Nejad [207] into the sleeves and the front of a shirt, as shown in Figure 6b. Wölfel [245] projected feedback onto a wall before the user. They used an anthropomorphic flower that imitates the user's posture. Even though they work visually, ambient lights and projections are more comparable to aural and vibrotactile feedback regarding privacy, as other people around the user could easily see their light.

(a) *van der Doelen et al. [232], ©NES 2011* **(b)** *©Soltani Nejad [207] 2018* **(c)** *Hong et al. [75], ©ACM 2015*

Figure 6: Examples of visual feedback using physical objects: LEDs on an enclosure attached to the side of a chair (a), LEDs attached to a shirt's sleeves and back (b), and an artificial flower that can bend its stem to mirror the user's posture (c).

We summarized eight less common approaches to visual real-time feedback in the category Other. Four publications present more straightforward methods, such as Duffy and Smeaton [47], who dimmed the monitor's brightness if the users had a bad posture. Others flashed the computer- [85] or smartphone- [123, 124] display to alert the user of a bad sitting posture. Shin et al. [198] explored a more complex method called "Relational Norm Intervention", which uses negative reinforcement and the desire of people not to disturb others. They, therefore, introduce a second person called "helper". The helper's phone gets blocked if the user sits in a bad posture and does not change it after receiving a vibrotactile notification. The helper can then send a push notification to the user, optionally with a text message. Finally, Dib and Sturmey [45] let an instructor model the correct posture to the participants.

Charts with sketch-like depictions were used together in three cases. Wang et al. [239] combined a dial chart for the angles of the back and head with a bell-shaped symbol. Min et al. [143] used a cartoon dog and status bars as described above. Flutur et al. [60] used a sketched human sitting on a chair with overlaid circles representing the used sensors. These circles' colors change based on the sensors' states, which were inactive, correct, moderate, and incorrect. Three other publications combined a chair sketch with a heatmap displaying pressure distribution [131, 140, 164], of which one example can be seen in Figure 5b. Charts have been combined with images and videos three times and once with text messages [209]. Jaimes [89] and Ishimatsu and Ueoka [84, 85] represented the user's posture with angled lines over live webcam footage.

We found six publications that combined sketch-like depictions with text messages. One example is the approach by Özgül and Patlar Akbulut [267], who showed cartoons and explanations of good and bad postures. Another one by Khurana et al. [101] showed an anthropomorphized giraffe whose neck angle and facial expression encode the user's posture. They, additionally, displayed general information about sitting posture and suggestions on how the user can improve theirs. While multiple publications showed sketches of a person on a chair with some information [151, 157, 224], Murata and Shibuya [151] added red circles around zones for which a bad posture was detected and provided additional information on how to correct them. Nizam et al. [157] showed arrows suggesting posture changes and a text explanation. The sketched human of Tavares et al. [224] adopted different postures while a text told the user that their stance was incorrect or suggested taking a break. Ochoa et al. [159] used an image of a human spine and added colored text labels for parts of the spine if the sensor of the corresponding section detected a bad posture.

Two publications combined physical objects with other feedback types. Haller et al. [70] created digital and physical flowers that imitated the user's posture and were able to shake themselves to motivate the user to do a training session. Hong et al. [74] combined an anthropomorphized flower with gamification in the form of points that can be used to customize the flower, badges that can be earned, and levels. Some of these features can be seen in Figure 5e. The system lets the user take care of the flower through proper sitting. Suggestive missions unrelated to sitting, such as cleaning the room or drinking water, were integrated. Finally, users can put fully grown flowers into a garden where they show statistics, and the user can start a new flower.

Finally, two publications combined more than two visual feedback types we defined. Shen et al. [196] created a heatmap of the pressure distribution, a bar chart of the sensors' pressure values, a sketch of a human representing the user's current posture, and a text message that encourages the user to do exercises or relax. Further, Speir [209] drew colored circles at the sensor positions on an image of their chair, using red for sensors that showed a deviation from the reference posture. An additional text suggested that the user should change their posture.

4.2 Active Correction

Out of the 104 publications featuring feedback, we found 14 that present feedback that actively corrects the user's posture. One example is the publication by Kiran et al. [105], who used Electrical muscle stimulation (EMS) to cause involuntary muscle contraction. Another approach by Ishimatsu and Ueoka [85] consists of a system that gives physical feedback by pushing wooden beads attached

(a) *Shen et al. [196], ©Springer Nature 2021* **(b)** *Shin et al. [200], ©ACM 2019* **(c)** *Fujita et al. [63], ©ACM 2021*

Figure 7: Examples of actively correcting the user's sitting posture: inflatable bladders on a chair (a), a self-adjusting computer display that can be tilted (b), and the combination of a self-adjusting chair that can be inclined and a sit-stand desk (c).

to sticks up the user's back. A further technique for active sitting posture correction is using bladders that can be inflated or deflated to improve the user's posture [117, 137, 154, 167, 196, 231], for example, Figure 7a.

Other researchers built systems that adjust the user's workstation to influence their posture directly or indirectly. One way is to move the computer monitor [197, 200] or the content in a Virtual Reality (VR) environment [199] to get the user to adjust their posture, for example, Figure 7b. Fujita et al. [63] built a chair that can change the angle of its seat, as shown in Figure 7c. Bailly et al. [13] developed an active workstation to move and rotate the keyboard, mouse, and monitor with actuators to avoid bad sitting postures. Wu et al. [253] used a Microsoft Kinect to measure the user's dimensions and calculate the optimal chair and desk height and positions for the keyboard, chair, and monitor. Using additional hardware that can actively change how someone is sitting is the most elaborate way to give feedback about sitting posture. We assume that such methods have disadvantages due to cost and size compared to other methods, while we also see a great advantage because they can improve the user's posture without their attention. This passive functionality might be crucial, for example, if the user has limited mobility or needs to focus on their current task, such as driving a vehicle.

4.3 Aural and Vibrotactile Feedback

Other non-visual feedback modalities are sound (aural) and vibration (vibrotactile), for which we found 32 and 33 papers, respectively. Most aural feedback was provided through simple sounds (e.g., [227, 249]), while others gave verbal instructions or warnings in person [45, 52, 64] or via recordings [40, 105, 149, 159]. Vibrotactile feedback was given through a single actuator (e.g., [17, 94]) or with multiple actuators to be able to focus the area where a deviation from a good posture was detected (e.g., [81, 82, 262, 263]). These types of feedback have the potential drawback of being heard by others. This is possible if audio is played through speakers or if the actuators of vibrotactile feedback are mounted in a way that amplifies the vibrating sounds, like on the wooden board of a chair. These sounds might disturb others, such as coworkers or family members, or make the user uncomfortable if others know about their need for feedback about sitting.

4.4 Evaluation of Sitting Posture Feedback Through User Studies

This section gives an overview of the publications evaluating sitting posture feedback. Of the 104 publications featuring feedback, 57 evaluated their approaches through 64 user studies. In the following, we provide some insights into their design, especially regarding their overall setup and the modalities studied. We first take a detailed look at the type of study, the duration, the number of participants, and the investigated measures. Then, we briefly summarize the studies' setups and results. A complete table with details of the studies can be found in the supplementary material.

4.4.1 Study types and tasks. We followed the classification of study types by Voit et al. [235] and identified 37 lab studies, 25 in-situ studies, one online, and one VR study. Study tasks were mainly related to regular PC tasks (51/64), such as specified tasks in typing (16/51), reading (6/51), and watching movies/playing games (2/51). In 31 cases, participants could do their own PC tasks. There were also sedentary tasks within special contexts (8/64), e.g., within schools [52], teens' daily life [124], or healthcare workers' tasks (5/8). Other tasks (6/64) focused mainly on testing or using the feedback.

4.4.2 Study duration and number of participants. Figure 8 shows the distribution of the studies' number of participants and their duration. Most studies comprised only one short session (40/64), and only 11 of the 24 studies that ran over multiple days had 12 or more participants. The average number of participants is 15, thus above the CHI average of 12 found by Caine [33]. For four studies, there is no information about the duration of the study, while for one, the number of participants was not stated clearly. These are not included in the charts. The time we report describes the time frame of a study, not only the intervention periods. Further, the maximum duration was taken in cases where the duration varied between participants. For example, the study by Dib and Sturmey [45] consisted of weekly 30-minute sessions over three to four months. This is depicted as a 4-month study in Figure 8, or in other words, as $4 * 30 * 24 = 2880$ hours ($months * days * hours$).

4.4.3 Measurements. We identified *posture behavior*, *usability/ User Experience (UX)*, *comfort*, *task performance*, and *open feedback* as categories for recorded evaluation data. Posture behavior (recorded

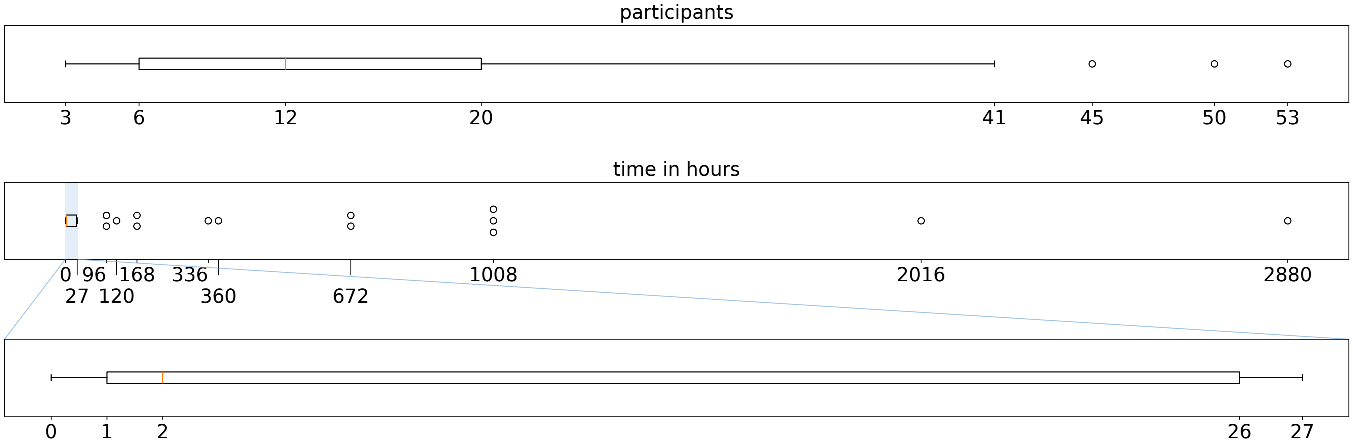


Figure 8: The distribution of the number of participants and the duration of the user studies evaluating sitting posture feedback in the literature. Please note that only 60 of 64 user studies are included, as four are missing one of the two displayed values.

by 54/64 studies) was analyzed through measurements of the posture, as well as subjective judgments of the participants. Usability/ UX (25/64) entailed questionnaires regarding the latter. Comfort (10/64) refers to measures regarding participants' sitting comfort or pain. Task performance (8/64) records the speed or accuracy of a primary task while sitting, self-monitoring, or correcting one's posture. Open feedback (10/64) comprised qualitative free-form answers in questionnaires or interviews. There are studies solely investigating posture guidance (27/64), usability (4/64), open feedback (2/64), or task performance (1/64). The others used a combination of those measures. Most studies report positive effects of feedback on these measures. We summarize the tendencies of these results in the following section. We are, however, not looking at the results in detail as the studies are very heterogeneous and lack standard definitions for (good) postures and methods to measure health improvements. We discuss this further in Section 5.2.

4.4.4 Feedback Details and Results.

Active. Active feedback was evaluated through 10 user studies. Four investigated approaches that move a (virtual) monitor to influence sitting posture [197, 199, 200], and two created an automatically adjusting workspace [13, 253]. Three studied an inclining chair [63], and one an inflatable chair to increase comfort [154]. Only two studies report mixed results regarding UX [63], while the rest present positive results for improving sitting posture and other measures.

Aural. Our review revealed four studies investigating aural feedback [11, 52, 180, 258], all of which used simple sounds to signal that the user should improve their sitting posture. Ribeiro et al. [180] and Epstein et al. [52] report mixed results regarding posture, while the rest found positive influences.

Vibration. Ten studies investigated vibrotactile feedback. Five studied setups with one source for vibration, while the others used up to 6 actuators to provide feedback where the users' posture needed improvement. One unique case we want to highlight is the second study by O'Brien and Azrin [158] investigating vibrating bone conductors. All studies evaluating changes in sitting posture reported positive results. Notably, Zheng and Morrell [264] did not measure the feedback's effect on sitting posture but reported a negative impact on the users' performance. The informal study by Johnson et al. [94] found increased posture awareness but mixed results regarding UX.

Visual. The most studied (15/64) single feedback modality is visual, with 15 out of the 64 studies. Real-time feedback was studied in all 15 studies, while two also studied summarized feedback. All types of visual feedback have been studied: text messages (4/15), sketch-like depictions (6/15), charts (4/15), images or videos (4/15), physical objects (3/15), and others (2/15). The studies investigating other types are by Murata and Shibuya [151], who investigated sitting scores comparing users, and Duffy and Smeaton [47], who dimmed the monitor's brightness. Five studies found mixed results [44, 201, 209, 241, 245], while the others reported a positive influence on posture, preference, comfort, and awareness.

Multiple Modalities. Most of the studies (25/64) incorporated more than one modality. Visual feedback is featured in most of these studies (22/25), followed by vibrotactile (16/25), aural (14/25), and active (4/25). In 13 cases, modalities were combined, while the other 12 studies conducted a comparative analysis. Of the studies that combined methods, two report mixed results [186, 202], while the rest describe a positive influence of their feedback on posture, preference, and UX. The comparative studies provide various interesting results. Four studies could not reveal significant differences between the compared methods [27, 263]. Three showed the advantage of combining multiple modalities over single ones [64, 67, 198]. Two studies revealed an advantage of active over visual [85, 105] and aural [105] feedback. The other studies found vibrotactile feedback to be more appropriate than aural [116], visual being preferred over aural [4], vibrotactile resulting in higher awareness while being more disruptive than visual, and a physical flower being less disruptive that a digital one [70].

5 DISCUSSION

Based on our review, we discuss our findings regarding sitting posture feedback and recognition in the following sections. We comment on the literature and suggest aspects to consider when building sitting posture systems. We further suggest and speculate about future research directions and reflect upon the limitations of our work. Our findings provide an overview of the topic and some guidance for future research.

5.1 Sitting Posture Recognition

Although many different approaches have been explored, most sitting posture recognition solutions in the literature use one type of sensor. The most prominent are Thin and Flexible Pressure Sensors (TFPS). They are usually built into a chair where the users do not see or notice them. They seem natural to measure weight distribution on a chair, are easy to use, can be made portable, and offer the broadest literature basis. The long-term popularity of such systems and high posture recognition accuracy make a strong case for their simplicity. Combinations of sensors, however, can offer more detailed posture data and additional measures. For example, wearable motion sensors or distance sensors at the backrest of a chair can complement TFPS with data about the user's back or other body parts. Some tasks might benefit from other combinations, like temperature and pulse sensors, as suggested by Kumar and Sridhar [109]. Vision-based setups can demonstrate their accuracy advantage when they are used to check and calibrate other systems, as suggested by Kappattanavar et al. [97]. The choice of hardware also depends on the user. For example, sensors that must be worn can be uncomfortable for some people. On the other hand, a mobile setup might be necessary for people who regularly sit in different or public places. The user's context can also be relevant, such as a work environment that does not allow cameras due to privacy issues. In general, we see the various approaches to measuring someone's sitting posture as a great strength of the field. One can choose the most fitting approach based on available space, cost, privacy, portability, and desired accuracy. **Thus, we suggest carefully considering the task and users before selecting sitting posture recognition technologies. Further, we suggest starting with a simple solution and only adding complexity as necessary.**

We further propose the field aims to integrate sitting posture recognition into existing devices like smartphones and wearable devices. This would greatly increase the spread and ease of use of the technology. Current wearable smart devices like watches and wristbands are already optimized for comfort, can detect movement, and suggest breaking up inactivity. To our knowledge, they cannot yet differentiate sitting postures. However, recent work by Mollyn et al. [147] shows the possibility of combining devices like smartphones, smartwatches, and earbuds to determine full-body posture. Future work should advance this technology and investigate its feasibility for accurate sitting posture recognition. **We recommend integrating posture recognition into existing devices to make it accessible to as many people as possible. This would also raise awareness of the influence of sitting posture on health and knowledge of better sitting habits.**

5.2 Sitting Posture Feedback

The most used feedback for sitting posture in the literature is visual (69/104), followed by vibrotactile (33/104), aural (32/104), and active (14/104). The strength of visual feedback lies in its versatility and the granularity of conveyable information. It includes blinking LEDs, physical objects that mirror the user's posture, and screen-based feedback. Visualizations on a screen can range from simple forms to temporal data on changes in posture over time. Additionally, numerous hardware options are available for conveying this information, including standard monitors, mobile devices, and simpler solutions such as an Arduino. **Thus, we recommend visual feedback, especially for prototyping, as it is a straightforward solution with many possibilities.**

Visual feedback does, however, not outperform the other modalities. Additionally, depending on the user's capabilities, some modalities might not work at all. For example, visual or hearing impairments rule out the corresponding feedback. Active feedback, such as self-adjusting computer displays, is likely more expensive, but people with decreased mobility could greatly benefit from active systems such as self-inflating bladders. Active feedback additionally has a higher customization demand, which means that it will need to be more adaptable to each individual than, for example, visual feedback. For example, when adjusting the monitor height, the user's anatomy needs to be taken into account, which will, of course, vary depending on each individual. Aural feedback can be given with limited or no desk and screen space. Further, aural feedback highly depends on whether the environment allows for the use of speakers or headphones. Using speakers can disturb other people, while users with aural tasks might not be able to use aural feedback at all. These examples show the importance of knowing the users and their tasks when designing sitting posture feedback. **We suggest building modular and fully customizable feedback systems that can adapt to users' preferences and needs to provide a satisfying and motivating experience for the broadest range of individuals.**

We found several ways to recognize posture and offer feedback in the literature. A positive impact on various measures has been found. Many studies indicate a positive influence of sitting posture feedback on measures such as posture, awareness, and comfort [44, 151]. However, all 64 surveyed studies investigated the short-term effects of single solutions. Most frequently measured is some form of posture behavior, like compliance with a particular posture to the time spent in different postures. Although similar, these results are not necessarily comparable between the studies. Detailed insights about the interaction between the individual elements of feedback approaches and the vast aspects of users' health still need to be clarified. Due to the lack of comparability, it is not easy to draw general conclusions on the effectiveness of different feedback modalities. **Thus, better comparability of postures and their effects on health is needed to further our knowledge about the long-term effects.**

Further, it is interesting to note that none of the studies we found considered the usability and UX aspect, which means there is an opportunity to delve deeper and gain valuable insights. Tasks outside of office work are rarely studied, but we see the potential for future work in sitting posture guidance systems beyond office work.

Private use, schools, and demanding occupations like healthcare or truck driving could greatly benefit from sitting posture feedback. From the technological side, we see potential for using mixed reality and wearable devices. **We suggest future work to explore sitting posture feedback in the context of usability, settings other than offices, and an even broader range of output technologies.**

To advance the field toward comparability and gain more general insights, we recommend addressing a series of open questions:

- Which postures are considered good or bad?
- How many postures must be distinguished to define healthy and unhealthy sitting behavior?
- As recent research suggests, is changing postures frequently and taking breaks enough to sit healthy?
- What impact does the duration of sitting have on the healthiness of a posture?
- How can we measure the influence of different sitting behaviors on health?
- Can we measure and isolate the effects of interventions and compare them?
- Which recognition technologies can identify all the required postures, and are they consistent with each other?

Once we have established these aspects, we can study the long-term effects of feedback on sitting posture and overall health:

- How long do the potential positive effects last? Do we need to use these systems periodically, only once for a certain amount of time, or constantly? In other words, do we need a permanent augmentation or only temporary guidance to improve our sitting?

We see the need for cross- and inter-disciplinary research between the HCI and the medical community to answer these questions and advance the positive influence that sitting posture recognition and feedback can provide.

5.3 Limitations

Using a systematic approach to conducting a literature review, like PRISMA[4] or QUOROM [146], has advantages but also limitations. The PRISMA guidelines were developed for the medical field and are, as argued by Rogers and Seaborn [183], "not actually appropriate for [HCI]." We also followed their recommendation to search multiple databases at various times. We looked through all the citations and references of the publications we identified as relevant to sitting posture recognition or feedback. However, the main drawback of our approach is that we did not document all exclusions properly, which is a disadvantage compared to PRISMA. In conclusion, we support and encourage the discussion about systematic reviews in HCI [183, 212] and hope for clear and useful guidelines for our community. While our citation and reference search method offers significant benefits, we urge anyone not following PRISMA to document all excluded papers meticulously.

6 CONCLUSION

Our work presents a literature review (N=223) on sitting posture recognition and feedback. We contribute an extensive overview and categorization of various types of hardware for recognition, feedback modalities, and visual feedback types. Further, an overview of user studies evaluating visual feedback is provided. We also offer detailed tables for all of these aspects. Our findings include the prevalence of pressure sensors and visual feedback. However, we found advantages and disadvantages inherent to all techniques and no one-size-fits-all solution. Less-used technologies are not necessarily less effective; it depends on the use case. The same also applies to feedback. We suggest offering various methods and customizability for the users, as their needs are crucial. Existing user studies indicate positive results but focus on single solutions and short-term effects. We provide open questions to advance our knowledge about recognizing sitting posture and giving feedback that can improve users' health in the long term. There is great potential in recognizing sitting posture and giving feedback to lessen the adverse health effects of the increasing time we spend sitting, whether voluntary, presupposed by certain occupations, or necessary due to limited mobility. Current statistics and trends about sitting time show that this topic will gain even more significance. We hope our contribution will stimulate and drive further research in this area.

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