Context-aware systems for chronic disease patients: A scoping review

Liliana Laranjo*, Huong Ly Tong*, Annie YS Lau¹, Kathleen Yin¹, A. Baki Kocaballi¹, Paige Martin¹, Sanjyot Vagholkar², Enrico Coiera¹

*LL and HLT both contributed as first authors

Corresponding author: Liliana Laranjo
Australian Institute of Health Innovation, Macquarie University
2113 NSW Sydney Australia

liliana.laranjo@mq.edu.au
(+61) 2 9850 2426

¹Centre for Health Informatics, Australian Institute of Health Innovation, Macquarie University, Sydney, Australia

²Macquarie University Health Sciences Centre, Macquarie University, Sydney, Australia

Keywords: patient work, context-aware, context-sensitive, "Chronic Disease"[Mesh], "Self-Management"[Mesh]

Word count: 2,329 (excluding figures, tables and references)
ABSTRACT

Background: Context-aware systems, also known as context-sensitive systems, are computing applications designed to capture, interpret, and use contextual information and provide adaptive services according to the current context of use. Context-aware systems have the potential to support patients with chronic conditions, yet little is known about how such systems have been utilized to facilitate patient work.

Objective: To characterize the different tasks and contexts in which context-aware systems for patient work were used, as well as to assess any existing evidence about the impact of such systems on health-related process or outcome measures.

Methods: Six databases (Medline, Embase, CINAHL, ACM Digital, Web of Science and Scopus) were scanned using a predefined search strategy. Studies were included in the review if they: focused on patients with chronic conditions; involved the use of a context-aware system to support patients’ health-related activities; and reported the evaluation of the systems by the users. Studies were screened by independent reviewers, and a narrative synthesis of included studies was conducted.

Results: The database search retrieved 1478 citations; 6 papers were included, all published from 2009 onwards. The majority of the papers were quasi-experimental and involved pilot and usability testing with a small number of users; there were no randomized controlled trials (RCTs) to evaluate the efficacy of a context-aware system. In the included studies, context was captured using sensors or self-reports, sometimes involving both. Most studies used a combination of sensor technology and mobile applications to deliver personalized feedback. Three studies examined the impact of interventions on health-related measures, showing positive results.
**Conclusions:** The use of context-aware systems to support patient work is an emerging area of research. RCTs are needed to evaluate the effectiveness of context-aware systems in improving patient work, self-management practices, and health outcomes in chronic disease patients.
INTRODUCTION

As health care moves from the traditional hospital setting to the personal sphere of home and community, individuals are increasingly being encouraged to engage in self-care [1,2]. Sociologists refer to this act of self-care as ‘patient work’, which involves effort and investment of time on the part of patients or family members to accomplish a health goal [3]. Patient work extends beyond strictly health-related tasks and is shaped by the context of patients’ lives and their daily routines [1]. It has been suggested that the use of context-aware technologies may thus better support patient work and improve self-care, as contextual information could trigger more personalized and relevant services or information [4].

Context-aware systems, also known as context-sensitive systems, are computing applications designed to capture, interpret, and use contextual information and provide adaptive services according to the current context of use [4,5]. Context-aware systems may thus harness everything from sensors that capture data indicative of context (such as time, location, light intensity), to inference mechanisms that interpret and action such data [5]. Even though context-aware systems have been piloted in some health care settings, their impact on health care outcomes remains unclear. Specifically, context-aware systems have mainly been piloted in the hospital setting [4] and for primary prevention [6-8] rarely addressing the context of chronic disease patients’ health-related activities in everyday life.

The aim of this review is to examine existing literature on interventions using context-aware technologies that support ‘patient work’. Specifically, we sought to characterize the different tasks and contexts in which such systems were used, as well as assess any existing evidence about their impact health-related process and outcome measures.
METHODS

Search strategy

A systematic search of the literature was performed in September 2016 and updated in October 2017, on Medline, Embase, CINAHL, ACM Digital, Web of Science, and Scopus, using search terms regarding patient work, context awareness and consumer health informatics. The complete search strategy is available in Supplement 1. The reference lists of relevant articles were also screened to ensure that all eligible studies were captured. A grey literature search was performed using Google Scholar to capture dissertations, theses, and conference proceedings that met the inclusion criteria.

Study selection criteria

In the scope of our study, we focused on context-aware systems that were capable of: i) capturing and processing contextual information (e.g. environmental data, user-related features); and, ii) using the captured contextual information to provide adaptive services and support patient work tasks in everyday life, either at home or in the community.

Studies were included in the review if they: focused on patients with chronic conditions; involved the use of a context-aware system to support patients’ health-related activities; and reported the evaluation of the systems by the users.

Studies were excluded if they were not in English or if they focused on healthcare providers instead of consumers. We also excluded interventions that merely gathered and displayed context information, without using it to adapt system behavior (passive context-awareness), as this was outside the scope of this paper.
**Paper screening process**

We conducted a two-phase screening process, initially excluding papers based on their titles and abstracts using a standard screening form, and then re-screening the remaining papers based on the full-text article.

Both phases were conducted by teams of two independent reviewers (two teams in the first phase and one in the second). Cohen’s kappa was used in the full-text paper screening to measure inter-rater agreement. Any disagreements in the screening were resolved through discussion and consensus.

**Data extraction and synthesis strategy**

One reviewer extracted information from the eligible studies into a data extraction form. Two other reviewers examined the completed form for consistency and accuracy. The following information was collected: first author, year, health domain, study type, participants’ characteristics (number, age, sex ratio), intervention characteristics, health activities (tasks undertaken by patients to achieve health goals), and main findings. To explore how context was utilized by the included studies, we analyzed the related contextual elements, based on previous work [4,9]. Context information was grouped into the following dimensions: setting (indoor or outdoor), environmental features (indoor and outdoor attributes, e.g. room temperature, humidity, air pollen), and user features (user-related data captured by the system, e.g. physical activity, physiological measurements, mental state). Time is also considered an important element but it is often coupled with other dimensions, so it was not analyzed separately in this review. Finally, we characterized the utilization of context for each study (i.e. the adaptive services provided by the system based on contextual data).
Our study design follows the guidelines for a scoping review proposed by Arksey & O’Malley (2005), and follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement [10], where applicable.
RESULTS

The database search retrieved 1478 citations; 607 duplicates were removed (Figure 1). After screening the abstracts and titles, 768 articles were excluded for not meeting the eligibility criteria. Full-text screening eliminated 36 articles (a list of excluded articles is available in Supplement 2). An additional two articles were found via hand-search, yielding 6 included studies in total. The kappa statistic measuring inter-rater agreement for full text screening was 0.6 (moderate agreement) [11].

Description of included studies

The number of participants in studies ranged from 4 to 47 (Table 1). One study was conducted in Canada [12], 2 were in the US [13,14], and 2 in Europe [15,16]. Most articles were published after 2010, except one [17]. The health domains covered in the studies included asthma [13], cardiovascular disease [16], kidney disease [12], Parkinson’s disease [17], diabetes [15], and mental health [14]. All included studies used quasi-experimental study designs to pilot test different context-aware systems. Demographic information on participants was often missing and inconsistently reported. Specifically, age data was reported by three studies [12,14,17] and four studies reported sex data [12,14,15,17].

Context elements and technologies of current interventions

The contextual elements of each included study are summarized in Table 2. Two studies focused on indoor settings [13,17] and 4 studies involved both indoor and outdoor settings [12,14-16]. Context was captured using sensors [12-14,16,17] and self-reports [12-15]. One particular study used ecological momentary assessment to capture self-reported data on social context, activity, and internal states (i.e. mood) [14]. Sensors captured data on location, ambient light [14], air quality [13], room temperature [16], and physiological measures [blood pressure (BP), heartrate,
skin temperature, cardiac function, exhaled nitric-oxide] [12,13,16]. Acceleration sensors were used to track movement and physical activity [16,17].

Most studies used a combination of sensor technology and mobile applications, where the sensors collected context information and the apps utilized those data to deliver personalized feedback [12-14,16]. Only one study did not involve the use of sensors, collecting contextual information solely through user self-reports [15]. In another intervention, a sensor was used without a mobile app, where context was harnessed with the help of a wearable computer, and earphones delivered auditory cues to improve gait performance in Parkinson patients [17].

**Health activities and health-related measures**

Self-monitoring was the most frequent health activity supported by context-aware systems in the included studies, where the collected data was then used to provide personalized feedback. Self-monitored data included physiological measures (e.g. BP) [12,13,15,16], symptoms [12-14], and lifestyle behaviors [15]. Other health activities included tracking lab test results [12], managing medications [12,15], and practising specific behaviours (e.g. overcoming freezing of gait) [17]. Only three studies reported the impact of the intervention on health-related measures [12,14]. Specifically, Bächlin found that the intervention had a sensitivity of 73.1% and a specificity of 81.6% in detecting freezing of gait events [17]. Ong et al. found statistically significant reductions in home blood pressure (BP) readings between baseline and after-intervention [systolic BP: -3.4 mmHg, 95% confidence interval (CI) (-5.0, -1.8); diastolic BP: -2.1 mmHg, 95% CI (-2.9, -1.2)] [12]. Burns et al. found a significant decrease in self-reported depressive symptoms ($P < .001$, per-protocol Cohen $d = 3.43$) and comorbid anxiety symptoms ($P < .001$, per-protocol Cohen $d = 2.58$) [14]).
No studies mentioned a thorough evaluation of patient safety problems. Four studies highlighted technical issues such as system downtime [15], battery drainage problems [13,14], and wearable sensor issues in activity detection [16].

<table>
<thead>
<tr>
<th>Database</th>
<th>n</th>
</tr>
</thead>
<tbody>
<tr>
<td>Medline</td>
<td>172</td>
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<tr>
<td>Embase</td>
<td>250</td>
</tr>
<tr>
<td>CINAHL</td>
<td>45</td>
</tr>
<tr>
<td>ACM Digital</td>
<td>151</td>
</tr>
<tr>
<td>Web of Science</td>
<td>430</td>
</tr>
<tr>
<td>Scopus</td>
<td>430</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>n = 1478</strong></td>
</tr>
</tbody>
</table>

607 duplicates removed

Title and abstract screening N= 808

772 records removed based on title/abstract

Full text screening N= 36

32 articles removed for not meeting inclusion criteria

Articles included after full-text review N= 4

2 articles included from hand-search

Articles included in the scoping review N= 6
Figure 1: Flow diagram of included studies
<table>
<thead>
<tr>
<th>Study author, year, location</th>
<th>Health domain</th>
<th>Study type; duration</th>
<th>N total [mean age, % female]</th>
<th>Health activities</th>
<th>Patient-facing technologies</th>
<th>Functions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bächlin et al., 2009, Israel [17]</td>
<td>Parkinson’s Disease</td>
<td>Quasi-experimental; NR</td>
<td>10 patients [66.4, 30%]</td>
<td>Self-management of gait deficits in Parkinson patients</td>
<td>Acceleration sensors</td>
<td>• Detect movement and freezing of gait</td>
</tr>
<tr>
<td>Ong et al., 2016, Canada [12]</td>
<td>Chronic kidney disease</td>
<td>Quasi-experimental; 6 months</td>
<td>47 patients with chronic kidney disease [59, 47%]</td>
<td>Self-management of chronic kidney disease (self-monitor BP and symptoms; manage medications; track lab test results)</td>
<td>Wireless BP monitor</td>
<td>Mobile application</td>
</tr>
<tr>
<td>Lamprinos et al., 2016, Germany and Turkey [15]</td>
<td>Diabetes</td>
<td>Quasi-experimental; 6 weeks</td>
<td>In Germany: 21 patients [NR, 24%]; In Turkey: 39 patients [NR, 45.5%]</td>
<td>Self-management of diabetes (self-monitor physiological measures; manage medications and lifestyle behaviors)</td>
<td>Mobile application and website</td>
<td>• Self-monitor (e.g. blood glucose, weight, BP, medication, physical activity, diet, sleep)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Mobile application</td>
<td>• Detect room temperature</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Mobile application</td>
<td>• Retrieve sensor data</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>• Trigger an alarm when an abnormal heart</td>
</tr>
<tr>
<td>Study</td>
<td>Condition</td>
<td>Design</td>
<td>Participants</td>
<td>Intervention</td>
<td>Technology</td>
<td></td>
</tr>
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</tr>
<tr>
<td>Anantharam et al, 2015, US [13]</td>
<td>Asthma</td>
<td>Quasi-experimental; 10 days</td>
<td>4 children [NR]</td>
<td>Self-management of asthma (self-monitor symptoms and identify triggers)</td>
<td>Indoor sensor: • Monitor environmental and air quality observations (e.g. pollen levels, carbon monoxide, temperature, humidity)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Exhaled air sensor: • Monitor exhaled nitric-oxide (indicator of inflammation)</td>
<td>Mobile application: • Gather and display sensor data • Record users’ observations (e.g. asthma-related symptoms) via questionnaires • Personalized feedback</td>
<td></td>
</tr>
<tr>
<td>Burns et al., 2011, US [14]</td>
<td>Major depressive disorder</td>
<td>Quasi-experimental; 8 weeks</td>
<td>8 patients [37.4, 88%]</td>
<td>Self-management of depression (self-monitor symptoms and identify triggers)</td>
<td>Mobile phone sensors: • Collect data on location, ambient light, phone usage Website: • Provide behavioral therapy • Display data collected from the smartphone Mobile application: • Collect self-reported data on social context, activity, location, and internal states (i.e. mood) via ecological momentary assessment • Integrate self-reports with sensor data • Personalized feedback • Predict patient states based on self-reports and sensor data</td>
<td></td>
</tr>
</tbody>
</table>

Abbreviations: BP, blood pressure; NR, not reported
<table>
<thead>
<tr>
<th>Study</th>
<th>Settings</th>
<th>Environmental features</th>
<th>User features</th>
<th>Utilization of context</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bächlin 2009</td>
<td>Indoor</td>
<td>None</td>
<td>Movement tracking</td>
<td>Real-time movement tracking system triggering cueing sound upon detection of freezing of gait.</td>
</tr>
<tr>
<td>[14]</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ong 2016</td>
<td>Indoor and outdoor</td>
<td>None</td>
<td>Blood pressure</td>
<td>Provide real-time personalized feedback on BP (e.g. uncontrolled BP triggered reminder messages recommending an increase in frequency of self-monitoring).</td>
</tr>
<tr>
<td>[12]</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Lamprinos 2016</td>
<td>Indoor and outdoor</td>
<td>None</td>
<td>Physical activity tracking (step counts), sleep tracking, blood glucose, blood pressure, weight, mood, nutrition</td>
<td>Creates a personalized action plan based on patient recorded data and generates self-management recommendations.</td>
</tr>
<tr>
<td>[15]</td>
<td></td>
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<tr>
<td>Zhang 2016</td>
<td>Indoor and outdoor</td>
<td>Room temperature</td>
<td>Physical activity tracking (standing, walking, running, jumping, walking upstairs/downstairs), heart rate, skin temperature, cardiac function, pulmonary function, posture</td>
<td>Trigger an alarm when an abnormal heart beat is detected.</td>
</tr>
<tr>
<td>[16]</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Anantharam 2015</td>
<td>Indoor</td>
<td>Carbon monoxide,</td>
<td>Exhaled nitric-oxide, asthma-related symptoms (e.g. coughing, chest tightness)</td>
<td>Provide personalized actionable recommendations based on sensor data and patient-reported information (e.g. identify and alert patients regarding triggers).</td>
</tr>
<tr>
<td>[13]</td>
<td></td>
<td>temperature, humidity, pollen levels</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Burns 2011</td>
<td>Indoor and outdoor</td>
<td>Location sensing, ambient light</td>
<td>Physical activity tracking, social context (e.g. interactions with other people), and internal states (mood, intensity of discrete emotions, fatigue, sense of accomplishment, concentration and engagement, and perceived control over current activities); Manually self-reported via ecological momentary assessment</td>
<td>Predict patient states based on self-reported and sensor data (using machine learning), displaying them on the mobile application. Future iterations will involve the use of predicted states to provide real-time interventions.</td>
</tr>
<tr>
<td>[13]</td>
<td></td>
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</table>

Abbreviations: BP, blood pressure
DISCUSSION
Main results

To the best of our knowledge, this is the first systematic scoping review to examine context-aware interventions to support patient work. The emerging nature of the field is reflected in the small number of included studies, their recent time of publication (all after 2010), and the predominance of quasi-experimental study designs. The majority of the papers involved pilot and usability testing with a small number of users; there were no RCTs to evaluate the efficacy of a context-aware system. In the included studies, context was captured using sensors or self-reports, sometimes involving both. Most studies used a combination of sensor technology and mobile applications to deliver personalized feedback. Three studies examined the impact of interventions on health-related measures, showing moderate-to-good sensitivity and specificity in detecting freezing of gait events in Parkinson patients [17], as well as significant improvements in BP [12] and reductions in depression symptoms and comorbid anxiety symptoms [14].

Comparison with previous literature

Other reviews have looked at the use of context awareness in health care [4,18]. Bricon-Souf (2007) found that there was a large gap between the requirements expressed by users, and the context-aware prototypes developed. Additionally, they reported that there was no consensus in the research community on how to model context and architectures to support its use. Similarly, Orwat et al. revealed that most systems were described in their prototype stage, and that implementation issues were rarely mentioned.

Our review, though only focused on patient work, also revealed comparable findings. Most studies described prototypes, and only three studies examined the impact of interventions on health-related measures, showing promising results in detecting freezing of gait events in Parkinson patients [17], as well as in improving BP [12] and depression and anxiety symptoms [14]. The use of context-awareness systems in patient work interventions has the potential to facilitate self-monitoring and improve the relevance and quality of the feedback provided, personalizing it to better fit participants’ context[12-14,16]. This sort of “just-in-time” support [19] has the potential to facilitate
patient work and improve the self-management of chronic conditions, by providing the advice patients need to make health management decisions at the right time, on a daily basis. Ameliorating self-management practices is a cornerstone of quality improvement efforts in chronic disease care, and is associated with better health outcomes in several conditions, like type 2 diabetes [20]. The costs and risks of using context-aware systems for patient work were rarely reported in the included studies. Four studies highlighted technical issues such as system downtime [15], battery drainage problems [13,14], and wearable sensor issues in activity detection [16]. No studies mentioned a thorough evaluation of patient safety problems. Future studies should consistently report unintended effects and possible harms of the systems, such as privacy, technical issues or any other unanticipated incidents [21].

Strengths and limitations

This systematic scoping review has several strengths in terms of study design. Firstly, an extensive search was performed across multiple databases to ensure that all relevant studies were captured. Secondly, the screening form was pre-tested and piloted before screening. Thirdly, all full-text papers were screened by two independent reviewers. Fourthly, the kappa score of 0.6 for the full-text screening phase revealed an acceptable level of agreement.

The results of our study need to be interpreted in light of some limitations. Given that this is an emerging field in health informatics, there is a lack of longitudinal and experimental studies, which hampers the evaluation of the impact of these interventions. This is the reason why a systematic scoping review was conducted, instead of a systematic review.

Another limitation was the exclusion of non-English papers. Even though this was conducted to ensure that all the authors could adequately understand and make an informed decision based on the abstracts, we might have missed important papers on patient work.

Implications for research and healthcare

The use of context-aware systems to support patient work is a promising area of research, as these interventions have the potential to facilitate self-monitoring and provide personalized just-in-time
feedback based on users’ characteristics and environmental features, with the aim of improving disease management and clinical outcomes. Specifically, the increasing use of sensors to automatically collect context information could eliminate the need for self-reporting and manual data entry, streamlining the task of self-monitoring for chronic disease patients [22]. Furthermore, future applications of artificial intelligence have the potential to expand on the current capacity of these systems to provide personalized and relevant services to individuals [23], better supporting users with their health-related tasks, and decreasing the burden of patient work.

Randomized controlled trials evaluating the effectiveness of context-aware systems in improving patient work, self-management practices, and clinical outcomes in chronic diseases. A common issue in context-aware systems research is the challenge of evaluating their real-world implementation [4,18]. Implementation fidelity is "the degree to which programs are implemented as intended by the program developers" [24]. It is known that implementation settings play a crucial role in the effectiveness of interventions, an issue that is at the core of implementation science’s efforts to model the impact of context on outcomes [25]. In order to allow for implementation fidelity and replicability, studies of context-aware systems should describe the setting explicitly, as well as provide sufficient details about the intervention and any potential adaptations for it to fit a different setting [26,27].

Conclusion

The use of context-aware systems to support patient work is an emerging area of research. Randomized controlled trials are needed to evaluate the effectiveness of context-aware systems in improving patient work, self-management practices, and health outcomes in chronic disease patients. Future studies should consistently report the intervention and the settings in which the intervention is being implemented.

Acknowledgements: The authors would like to thank Mr Duy Hung Nguyen and Ms Keyu Wang for their assistance in the manuscript format.

Conflict of interest: The authors declare no conflicts of interest.
**Funding:** This research was supported by the National Health and Medical Research Council (NHMRC) grant APP1134919 (Centre for Research Excellence in Digital Health) and Program Grant APP1054146.

**Author contribution:** Study design: AYSL, SV, EC; Search strategy: HLT, LL, AYSL; Screening: HLT, LL, KY, PM; Data extraction: HLT, LL, ABK; First draft: HLT, LL, AYSL, KY, ABK, EC; Revision and subsequent drafts: HLT, LL, AYSL, KY, ABK, PM, SV, EC

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