Current Digital Interventions for Urinary Tract Infection Prevention and Management in Persons Living with Dementia: A Scoping Review

Kuan-Ching Wu, Basia Belza, Donna Berry, Frances Lewis, Oleg Zaslavsky

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Table of Contents

Original Manuscript 4
Supplementary Files 31
Figures 32
Figure 1 33
Figure 2 34
Figure 3 35
CONSORT (or other) checklists 36
CONSORT (or other) checklist 0 37

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Abstract

Background: Older adults with dementia are at higher risk of hospitalized for urinary tract infections (UTIs), with worse health outcomes. Digital interventions, such as smartphone apps, wearable devices, and telehealth, hold promise for improving UTI detection, monitoring, and prevention. However, their effectiveness for people with dementia and their caregivers remains unclear.

Objective: This review aims to identify: 1) The types of digital interventions and devices used for UTI management and prevention in people with dementia and their caregivers; and 2) The outcome variables and key findings of these interventions.

Methods: A scoping review was conducted using the PRISMA-ScR framework, searching PubMed, CINAHL, Embase, IEEE Xplore, and Web of Science for studies from 1998 to 2024. The review included quantitative, qualitative, and mixed-method studies that described digital interventions for UTI management in persons with dementia. Studies were excluded if they lacked detailed intervention descriptions or outcome reporting. Data were charted and summarized to address the study aims.

Results: Seven studies were included from 1800 screened. Three digital interventions were evaluated: Technology Integrated Health Management (TIHM), a real-time locating system (RTLS), and a smart diaper system (SDS). The TIHM and RTLS showed high effectiveness in UTI detection, with sensitivities up to 91%, while the SDS had lower sensitivity.

Conclusions: The review highlights the potential of sensor-based technology and AI in early UTI detection. However, most interventions lack theoretical foundations and preventive strategies, suggesting a need for more comprehensive approaches involving caregivers and clinical guidelines. Clinical Trial: https://doi.org/10.17605/OSF.IO/G2SZW

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Original Manuscript

Current Digital Interventions for Urinary Tract Infection Prevention and Management in Persons Living with Dementia: A Scoping Review

***Ethical Approval: Ethical approval was not required for this scoping review as it does not involve the collection or analysis of primary data. All information was obtained from publicly available sources and published literature.*

Abstract

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Older adults with dementia are at higher risk of hospitalized for urinary tract infections (UTIs), with worse health outcomes. Digital interventions, such as smartphone apps, wearable devices, and telehealth, hold promise for improving UTI detection, monitoring, and prevention. However, their effectiveness for people with dementia and their caregivers remains unclear.

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The review highlights the potential of sensor-based technology and AI in early UTI detection. However, most interventions lack theoretical foundations and preventive strategies, suggesting a need for more comprehensive approaches involving caregivers and clinical guidelines.

Keywords:

digital intervention, AI algorithms, dementia care, urinary tract infections, prevention, hospitalizations

Introduction

Urinary tract infections (UTIs) refer to infections localized in any part of the urinary tract and can occur in individuals throughout their lifetime. Older adults living with dementia were 3.4 times more likely to be admitted to hospital or visit the emery room (ER) for UTIs and experience worse health complications (e.g., increased risk of delirium, cognitive decline, and higher mortality rates) compared to patients without dementia [1], [2], [3], [4], [5]. UTIs also impose high societal costs on the healthcare system and add significant caregiving burdens for persons with dementia and their family caregivers (FCGs) [6]. Therefore, effective UTI prevention and management are crucial for avoiding unnecessary hospitalizations, preventing future admissions, and enhancing the well-being and longevity of persons living with dementia and their FCGs [7].

Current approaches for UTI prevention and management in persons living with dementia typically include antimicrobial therapy, hydration, and hygiene practices [7], [8], [9]. However, these traditional methods face significant challenges. Recognizing UTI symptoms can be difficult due to communication barriers and atypical symptom presentation in this population [7], [9], [10]. Caregivers often rely on non-verbal cues and observation to detect potential infections [7], [11]. Additionally, memory issues and difficulties adhering to medication schedules in persons with dementia complicate the management of treatment regimens, including antibiotic therapy [12], [13]. Communication barriers further hinder effective interactions between healthcare providers, caregivers, and persons with dementia [11], [14]. A collaborative approach, involving healthcare professionals and caregivers, is essential to developing tailored care plans that prioritize UTI prevention and management while addressing these challenges [7].

Digital health interventions have shown promise in disease management, risk factor prevention, reducing caregiver burdens, and promoting healthy behaviors in persons living with dementia and their caregivers [9], [15], [16], [17]. Digital devices, such as smartphone applications, wearable devices, and telehealth platforms [18], [19], have the potential to revolutionize UTI detection, monitoring, and adherence to preventive measures and treatment regimens [20], [21]. These technologies can facilitate remote monitoring of hydration levels, provide reminders for medication adherence, and offer educational resources for caregivers [20], [22]. Moreover, telehealth platforms enable virtual consultations, improving access to timely healthcare services for persons with dementia, especially in remote or underserved areas [23], [24].

While some studies have integrated UTI trainings, guidelines, or UTI symptom diaries into mobile and online interventions for healthcare workers or adult patients [25], [26], [27] , there remains a significant research gap regarding the role of digital interventions in UTI prevention and management for persons living with dementia and their caregivers, as well as the outcomes these interventions can achieve. Understanding the types of digital interventions described and tested in the current scientific literature for this population, along with their effectiveness in reducing the incidence of UTIs, is crucial. Digital interventions present promising opportunities to enhance UTI detection, monitoring, and adherence to preventive measures and treatment regimens. Embracing these interventions can significantly improve the quality of life and well-being of persons living with dementia and their caregivers.

To address this research gap, we conducted a scoping review to provide an overview of existing research on digital interventions designed for UTI prevention and management in community-dwelling persons living with dementia and their caregivers. Our research questions were: 1) What types of digital interventions and devices are described and tested in the current scientific literature for persons living with dementia and their caregivers to manage or prevent UTIs occurrences? and 2) What outcome variables are included and what are the key findings in current digital interventions for urinary tract infection (UTI) prevention and management in persons living with dementia and their caregivers?

Methods

This study utilized a scoping review as our methodological approach considering the broad nature of our research question, the heterogeneity of the studies we retrieved, the diversity in different stages (mild to severe stage) of the dementia population and their caregivers, and a lack of relevant comprehensive reviews in prior literature [28], [29]. We adhered to the steps of PRISMA-ScR framework protocol: (1) indicate whether a protocol and registration exist, (2) identify eligibility criteria, (3) locate information sources and search, (4) selection of sources of evidence, (5) chart data from the selected studies, and (6) synthesize results and reported our data following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) Checklist [29]. The study was registered prospectively with the Open Science Framework on April 26th, 2024 (see registration DOI: https://doi.org/10.17605/OSF.IO/G2SZW)

Eligibility Criteria

We included publications of quantitative, qualitative, or mixed methods that met the following criteria: 1) provided a description of interventions aimed at managing or preventing UTIs in persons living with dementia and their caregivers; 2) involved digital technological devices (such as sensors, computers, tablets, or mobile phones) delivered via the internet; 3) employed research designs including experimental, quasi-experimental (such as nonequivalent control and pre-post, nonequivalent control and post only, one group pre-post, and time-series designs), randomized controlled trials (RCTs), cohort studies, and feasibility studies with findings; 4) were published in English; and 5) were published from January 1998 to January 2024, taking into account the introduction of the first PubMed Mesh Term in 1999.

We excluded publications that met any of the following criteria: 1) focused solely on formative development of technology systems; 2) were not published in peer-reviewed journals; or 3) were case studies. Additionally, studies on technologies exclusively used by health professionals were excluded, as well as those reporting only on technical aspects or parts of a technology (e.g., interfaces or prototypes), systematic reviews, and study protocols.

Information Sources and Search

A comprehensive literature search was conducted in collaboration with a University of Washington Health Science Librarian within the five databases to identify all relevant literature: PubMed, CINAHL, Embase, IEEE Xplore, and Web of Science. Keywords and Medical Subject Headings (MeSH) terms were used regarding the concepts of digital intervention, dementia, urinary pathogens, and urinary tract infections. The following were specific keywords used in the PubMed searching strategies: ("Mobile Applications"[Mesh] OR "Computers, Handheld"[Mesh] OR "Internet"[Mesh] OR "Telemedicine"[Mesh] OR "Internet-Based Intervention"[MeSH] OR "Self-Help Groups"[Mesh] OR "Social Media"[Mesh] OR social media OR smartphone OR telehealth OR telemedicine OR health app OR mHealth OR eHealth OR eMedicine OR internet-based intervention OR web-based intervention OR online intervention OR computer OR internet OR "app based" OR “self help group” OR “support group”) AND (UTI OR urinary tract infection OR bacteriuria OR "Urinary Tract Infections"[Mesh]) AND ("Aged"[Mesh] OR "older adults" OR "elderly" OR "geriatric" OR "aging") ("Brain Diseases"[Mesh] OR "Neurocognitive Disorders"[Mesh] OR dementia OR cognitive impairment OR Alzheimer's OR brain disease OR cognitive disorder OR cognition disorder). Detailed search strategies are provided in *Multimedia Appendix 1*. We also conducted a reference check of the included studies to include potentially relevant studies.

Selection of Sources of Evidence

All citations were uploaded to Rayyan [30], a web-based research tool that helps researchers to collaborate in reviews and other knowledge synthesis projects. After duplicates were removed, 2 reviewers subsequently screened all the articles by title, abstract, and full text. The reviewers engaged in a process of cross reviewing their findings to mitigate any potential screening bias. In cases of disagreement, they engaged in discussions pertaining to the suitability of articles in relation to the research objectives and the predefined inclusion and exclusion criteria, with the aim of reaching a consensus. A third reviewer was included to solve any conflicts that arose during the title and abstract screening phase, and the full-text review phase.

Data Charting and Critical Appraisal

A data-charting table was generated to address the research questions and to guide the data abstraction process. The data-reporting table displays a summary of these study features: authors, study characteristics (year of publication, study design, country), sample characteristics (sample size, mean age, and gender ratio), study aims, intervention descriptions as well as intervention length, settings, dosages, type of technology involved, and main findings. We did not conduct a standardized critical appraisal of the included studies since our primary goals were to provide an overview and map out the topics.

Synthesis of the results

We presented the results through a structured and narrative synthesis, visually, and in tabular form. To answer our research questions, we grouped the aim, intervention & methodology, and key findings into Table 1. Additionally, we compared each study characteristics (year, author, country, research design), participant demographics (sample size, mean age, users), and the intervention settings and length from each included studies as presented in Figure 2. Finally, we grouped the technologies thematically in each study and reported in Table 2 to provide details regarding intervention name, description, data collected, dosage, and technological devices involved in the intervention.

Table 1. the aim, intervention and methodology, and key findings.

Authors/ Year	Aim	Data Source (Intervention)/ Method	Key Findings
Capstick et al., 2024	To propose a machine learning method that alerts clinicians to UTI[a] risk in subjects, enabling early detection and improved screening for treatment.	Minder Program: TIHM[b] for Dementia System of Care. Use *machine learning techniques* to calculate UTI risk and perform stratification on scores to support clinical translation and allow control over the balance between alert rate and sensitivity and specificity.	1. The proposed UTI model achieves a sensitivity of 65.3% (CI[c] 64.3–66.2) and specificity of 70.9% (CI 68.6–73.1) when predicting UTIs on unseen participants and after risk stratification, a sensitivity of 74.7% (CI 67.9–81.5) and specificity of 87.9% (CI 85.0–90.9). 2. This machine learning model alerts clinicians of UTI risks in subjects, enabling earlier detection and enhanced screening when considering treatment.
Bijlani et al., 2022	To develop an online unsupervised approach to detect UTIs and hospitalizations.	Minder Program: TIHM for Dementia System of Care Propose *CMP*[d], an unsupervised learning–based algorithm to detect anomalies representing adverse health conditions using activity changes in people living with dementia.	1. The CMP yielded, on average, 84.3% recall with 5.1% alert rate, offering the best balance of recall and relative precision when evaluated for UTIs and hospitalization. 2. This study proposed a high sensitivity and low alert rate model to detect anomalies and anomaly biomarkers in people living with dementia.
Ramazi et al., 2022	To develop and test how motor behaviors, delivered from location and movement sensor tracking data, may be associated with falls, delirium, and UTIs.	Real-time locating system Utilize *real time location system* data and *DL[e] techniques* (which are a family of advanced machine learning methods) to classify motor behaviors among LTC[e] residents with cognitive impairment or dementia for up to 18 months.	1. Motor behavior classifications were sensitive and specific to falls, delirium, and UTI predictions 1 week before the week of the event (UTI sensitivity = 0.91 (SD[f] 0.09); specificity range =0.71 (SD 0.04); precision = 0.76 (SD 0.04)). 2. Study findings suggest that falls have behavioral precursors that may be used to identify those in need of more timely exercise interventions. Study findings also support the idea that UTIs and delirium may be identified sooner in LTC through an objective study of changes in motor behaviors, which may improve treatment outcomes in this vulnerable population.

Table 1. the aim, intervention and methodology, and key findings.

Authors/ Year	Aim	Data Source (Intervention)/ Method	Key Findings
Cho et al., 2021	To evaluate the applicability of the smart diaper system for urinary detection, and its effect on IAD[g] occurrences in an acute care hospital.	Smart Diaper System The diaper has an absorbent liner inside and conductive lines on the outside connected to a sensor. When urine is absorbed, it increases electrical flow between the lines, allowing the sensor to detect and measure the amount of urine. This data is sent to a smartphone via Bluetooth. If the urine volume below/exceeds set limits (50 mL to 500 mL in this study), a caregiver is notified through a dedicated app. No algorithm reported.	1. The smart diaper system's voiding detection rate was lower than expected at 32.8%. However, it still promptly notifies caregivers of urination, aiding in timely diaper changes to prevent or improve incontinence-related issues like IAD and bed sores. 2. The smart diaper system functions effectively with researchers' assistance, but older caregivers may find it challenging to learn to use the system within the study's short three-day period.
Li, Rezvani, et al., 2021	To propose an attention model by using environmental sensors to predict incidents of UTI events and agitation in people with dementia.	Minder Program: TIHM for Dementia System of Care. Introduce an *attention-based, DL model* that can identify the important time steps and features and utilize long-distance dependencies to make better predictions. The proposed model provides a prediction based on the selected time points and the selected features from the raw observation and measurement data.	1. The proposed model provides a recall of 91% and precision of 83% in detecting the risk of agitation and UTIs. 2. This model can be used for early detection of conditions such as UTIs and managing of neuropsychiatric symptoms such as agitation in association with initial treatment and early intervention approaches.
Li, Kolanko, et al., 2020	To propose a semi-supervised model to make predictions of UTIs in dementia.	Minder Program: TIHM for Dementia System of Care Utilize a semi-supervised model (adaptive *DNN*[h] algorithms and *supervised probabilistic models*) that continuously learn from routinely collected in-home observation and measurement data. This model can process highly imbalanced and dynamic data to make robust predictions in analyzing the risk of UTIs in dementia.	1. The proposed model (semi-supervised model) achieves 85% recall with 86% precision. It proves that this model performs better than other existing models on detecting UTIs events.

Table 1. the aim, intervention and methodology, and key findings.

Authors/ Year	Aim	Data Source (Intervention) /Method	Key Findings
Enshaeifar et al., 2019	To propose an unsupervised algorithm to detect UTI occurrence from environmental data and physiological data collected via in-home sensory devices.	Minder Program: TIHM for Dementia System of Care. Develop algorithms (*NMF*[i] *& iForest*[j]**)** to detect UTIs: 1) extract latent factors from raw observation and use them for clustering and identifying the possible UTI cases. 2) detect changes in activity patterns to identify early symptoms of cognitive decline or health decline in participants.	1. The unsupervised machine learning model (NMF) is 10% more effective than the baseline model (SVM[k]), reducing false positive alerts for UTIs; the iForest presents 85% sensitivity to night-time activity. 3. This study proposed algorithms that enables: 1) early detection of UTIs; 2) identification of changes in daily activity patterns in people living with dementia.

Note:
[a]UTIs: urinary tract infections.
[b]TIHM: Technology Integrated Health Management.
[c]CI: Confidence Interval.
[d]CMP: Contextual Matrix Profile.
[e]DL: Deep Learning.
[e]LTC: Long term care.
[f]SD: standard deviation.
[g]IAD: incontinence-associated dermatitis.
[h]DNN: Deep Neural Network.
[i]NMF: Non-negative Matrix Factorization.
[j]iForest: Isolation Forest.
[k]SVM: Support Vector Machine.

Table 2. Intervention name, description, outcome variables, dosage, and technological devices involved in the intervention.

Name	Description	Outcome Variables	Dosage	Types of Technological devices
Technology Integrated Health Management (TIHM) [33], [34], [35], [36], [37]	A digital platform routinely collects longitudinal, observational, and measurement data, within the home and apply machine learning and analytical models for the detection and prediction of adverse health events affecting the well-being of persons living of dementia.	• Environment data from sensors • Physiological data (blood pressure, heart rate, body temperature, weight, hydration reading, urine samples)	-24/7* -Twice a day	• Sensor devices (infra-red (PIR) sensors, motion sensors, pressure sensors, door sensor, central energy consumption monitoring device) • Blue-tooth enabled medical devices (physiological monitoring devices that are used for submitting daily measurements of vital signs, weight and hydration) • Smart power plugs
Real time locating system (RTLS) [32]	A system which uses real-time data from technology consists of a wrist-worn tag (required for tracking multiple residents) and ceiling-mounted sensors to triangulate location in and around a unit and provide x, y, and z coordinates.	• Motor behaviors (location coordinates x, y, z)	-24/7*	• Wrist-worn tracking tag • Location sensor (ceiling-mounted)
Smart Diaper System [22]	A smart system that integrates a sensor-equipped diaper with a mobile app. The diaper collects urinary data, uploads the information to the app, and notifies caregivers.	• Urine record (volume& frequency) • Accuracy of urine output assessment, • Occurrence of IAD • User experience	-24/7* -24/7* -Once per Day	• Diaper with conductors • Sensor devices (current flow and pressure) • Smartphone with app

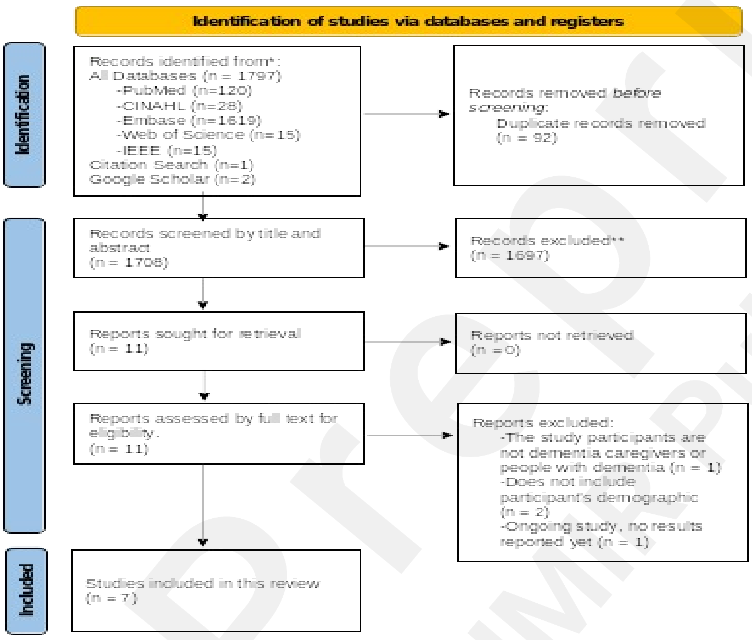
Note: 24/7*: 24 hours a day, 7 days a week; IAD: incontinence-associated dermatitis.

Results

Study Selection

The literature research produced a total of 1800 articles from five databases and other sources (citation search and Google Scholar). The databases search from the PubMed, CINAHL, Embase, IEEE Xplore, and Web of Science yielded 1797 results, 1 from the citation search and 2 from Google Scholar. Removing duplicates left 1708 articles. After abstract and title screening, 1697 irrelevant articles were removed, and 11 studies were retrieved for the full article review. In total, 7 articles were included in the final list after full article eligibility criteria were applied. The workflow is illustrated in *Figure 1* Prisma-ScR flow chart [31].

Figure 1. Prisma-ScR flow chart. The PRISMA-Scr (Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews) flow chart describes the process of selecting studies for inclusion in this scoping review.



Characteristics of the included studies, participants, and interventions

Figure 2 summarized the characteristics of the included studies, participants' features, and interventions in this scoping review.

Study Characteristics

Of the seven included studies, the articles were published from 2020 to 2024, with a surge in 2021-2022 (2 studies each year). Geographically, the United Kingdom accounts for 72% of the research (n=5), followed by the United States (n=1) and South Korea (n=1). Notably, all of the included studies were observational. One study was reported as a longitudinal study, and another as a prospective pilot study. None of the studies included a control group.

Participant Features

As depicted in Figure 2, the sample size of the participants varied between 15 and 117, with a mean of 63.0 and a standard deviation of 41.7. The mean age of the participants across all studies ranged from 79.9 (SD 11.2) years old to 84.0 (SD 6.1) years old. The age of the participants in most studies was around 80 years old. Overall, the mean age of the total participants averaged approximately 82.5 years old, with a standard deviation of 6.7 years old. Except for one single-sex studies [32], all other studies include both sexes, with a total of 230 (52.2%) males and 211 (47.8%) females. The target users in the included studies are primarily people with all stages of dementia and those with mild cognitive impairments. Only one study included dementia caregivers to the intervention [22].

Intervention Duration and Settings

Among the seven included studies, three distinct interventions were identified. The majority, 71.4% (n=5), were covered by the Minder program from the United Kingdom, also known as the "Technology Integrated Health Management (TIHM)" intervention. The other two interventions were the "Real-time Locating System" (n=1) from the United States and the "Smart Diaper System" funded by South Korea. In Figure 2, we present the distribution of intervention durations, which ranged from 4 to 3864 days. The mean duration was 804.3 days (SD = 1264.5 days), indicating a wide range in the duration of interventions across studies. In terms of the intervention settings, 71.4% (n=5) of the interventions were installed in participants' homes, while 14.3% (n=1) were conducted in hospital wards, and another 14.3% (n=1) were carried out in long-term care facilities. The length of the interventions in the trials included in this study varied widely. Forty-three percent (n=3) of the studies had an intervention length of over a year, while 57% (n=4) had an intervention lasting less than a year, with one study lasted less than a week and only tested a system, not the long-term effect of the technology.

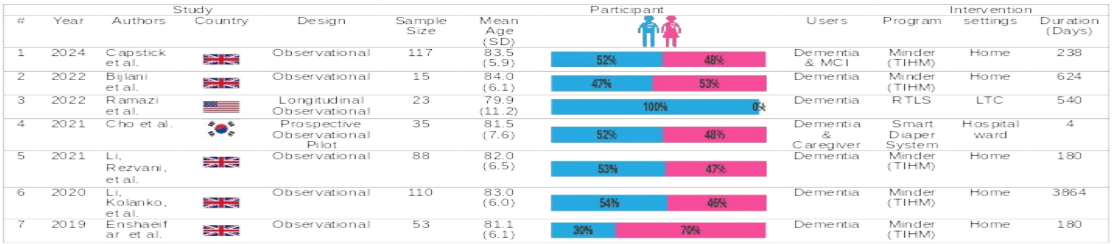
Synthesis of the results

Research Question 1: What types of digital interventions and devices were described and tested in the current scientific literature for persons living with dementia and their caregivers to manage or prevent UTI occurrences? This subsection along with Table 1 and Table 2 describe three types of digital interventions summarized from the included studies, methodology used in each study, and types of devices utilized in current scientific literature to assist the prevention and management of UTIs in persons living with dementia and their caregivers.

The Minder program [33], [34], [35], [36], [37] was funded by two institutions: the England National Health Service (NHS), and Innovate UK, the Technology Strategy Board, the United Kingdom's innovation agency. This program utilized Technology integrated health management (TIHM) for Dementia System of Care, an Internet of Things (IoT) technology to monitor individuals with dementia. Five studies utilized data from this intervention. This program collected data through environmental sensors and Bluetooth-enabled medical devices that tracked daily activities and vital signs (see Table 2) in persons with dementia. The environmental sensors included two passive infrared (PIR) sensors (installed in the hallway and living room), four motion sensors (one in the kitchen, one on the pill box/drawer, and two on the bedroom and bathroom doors), two pressure sensors (placed on the bed and the chair), one main entrance door sensor, and one central energy consumption monitoring device. Participants recorded physiological data twice a day using Bluetooth-enabled medical devices (e.g., blood pressure monitor, smart scale, heart rate monitor, thermometer). This information was relayed to a monitoring team via a computer-based alert system that used machine learning to identify health and social care concerns. The monitoring team contacted the patient or their caregiver to provide advice, and Dementia Navigators offered support for non-emergency issues. Participants were monitored 24/7 for six months or more. This intervention incorporated diverse AI algorithms, with aimed to promptly alert clinicians to patients' UTI risks and facilitate early detection of UTI occurrences.

Figure 2. Characteristics of the included studies, participants, and intervention.

The figure provides detailed information for each study, including the sample characteristics of the participants and the intervention details.



Study							Participant	Intervention			
#	Year	Authors	Country	Design	Sample Size	Mean Age (SD)		Users	Program	settings	Duration (Days)
1	2024	Capstick et al.		Observational	117	83.5 (5.9)	52% 48%	Dementia & MCI	Minder (TIHM)	Home	238
2	2022	Bijlani et al.		Observational	15	84.0 (6.1)	47% 53%	Dementia	Minder (TIHM)	Home	624
3	2022	Ramazi et al.		Longitudinal Observational	23	79.9 (11.2)	100% 0%	Dementia	RTLS	LTC	540
4	2021	Cho et al.		Prospective Observational Pilot	35	81.5 (7.6)	52% 48%	Dementia & Caregiver	Smart Diaper System	Hospital ward	4
5	2021	Li, Rezvani, et al.		Observational	88	82.0 (6.5)	53% 47%	Dementia	Minder (TIHM)	Home	180
6	2020	Li, Kolanko, et al.		Observational	110	83.0 (6.0)	54% 46%	Dementia	Minder (TIHM)	Home	3864
7	2019	Enshaeifar et al.		Observational	53	81.1 (6.1)	30% 70%	Dementia	Minder (TIHM)	Home	180

Note: MCI: mild cognitive impairment; TIHM: Technology Integrated Health Management; RTLS: Real-time locating system; LTC: long-term care.

Figure 2. Characteristics of the included studies, participants, and interventions

The Real-time locating system (RTLS) [32] was a longitudinal study approved by the Department of Veterans Affairs (VA) Research and Development Office in United States of America which integrated real-time data from technology and machine learning techniques to classify motor behaviors among long-term care residents with cognitive impairment or dementia for up to 18 months. The system consists of a wrist-worn tag (required for tracking multiple residents) and ceiling-mounted sensors to triangulate location in and around a unit and provided x, y, and z coordinates. The RTLS intervention aimed to utilized motor behavioral data to predict falls, delirium, and UTIs in persons living with dementia.

The Smart Diaper System [22] was a detection technology which utilized a smart diaper with conductor sensor devices to measure current flow, frequency, and integrated the information with an app that notified caregivers to change the diaper and measured voiding volume automatically. This system aimed to identify occurrences of incontinence-associated dermatitis (IAD) or aggravation of bed sores, conditions that may predispose patients to urinary tract infections (UTIs), within acute care settings.

Sensor Technology and Artificial Intelligence (AI) algorithms. Overall, sensors technology and integration with AI algorithms were applied in all the digital interventions (see Table 1 & Table 2) of our included studies. The devices included infra-red (PIR) sensor, motion sensors, door sensor, pressure sensor (e.g., sleep tracking mattress, urine flow), location sensors (coordinate), and a diaper sensor. Also, Bluetooth/Wi-Fi-enabled medical devices such as smart scale, thermometer, BPM Connect (a Wifi-blood pressure monitor) were widely used in 70% of the studies. While Cho et al. (2021) did not specify any algorithm used in the smart diaper system, Ramazi et al. (2022) described their use of a deep learning algorithm to classify motor behavioral data collected from RTLS, identifying falls, delirium, and UTIs. Several AI algorithms had been incorporated into TIHM studies for UTI risk analysis and prediction of UTI occurrence. Enshaeifar et al. (2019) introduced an unsupervised algorithm, Non-negative Matrix Factorization (NMF), to extract and analyze environmental and physiological data, along with a pattern analysis algorithm, Isolation Forest (iForest), to detect UTI occurrences. Li et al. (2021) presented a deep learning model for the early detection of UTIs or agitation in persons with dementia by providing predictions based on selected time points and features from raw observation and measurement data. Additionally, Li, Kolanko, et al. (2021) proposed a semi-supervised approach that leveraged the benefits of adaptive Deep Neural Network (DNN) algorithms and supervised probabilistic model. In a separate study, Li, Rezvani, et al. (2021) introduced attention-based, deep learning models to continuously learn from routinely collected in-home observation and measurement data to predict UTI risks in persons with dementia. Bijlani et al. (2022) developed a Contextual Matrix Profile (CMP), an unsupervised learning-based algorithm that detects anomalies (representing adverse health conditions) using activity changes in people living with dementia to better evaluate the risks of UTIs and hospitalization. Capstick et al. (2024) proposed a machine learning model that calculated UTI risk and stratifies scores to support clinical translation. This model alerted clinicians to UTI risk in patients, enabled early detection and improved screening for treatment.

Research Question 2: What outcome variables were included and what were the key findings in current digital interventions for UTI prevention and management in persons living with dementia and their caregivers? This subsection along with Table 1, Table 2, and Figure 3 describe the outcome variables measured in each intervention, results, and the key findings in each study.

Outcome Variables: In studies involving TIHM intervention, the outcome variables were divided into two categories: environmental data and physiological data. The environmental data referred to information collected by sensors installed in participants' homes, including activity patterns of their daily routines and nighttime sleep patterns [33], [34], [35], [36], [37]. These data were primarily gathered using motion, pressure, and door sensors. Each study developed its algorithms and models based on the sensory data utilized. For example, Bijlani et al. focused solely on PIR data, as it was the least missing, most reliable, and available with the finest granularity across the cohort [33], while other studies [34], [35], [36], [37] used combined sensory data to run their models. The physiological data collected by the medical devices were blood pressure, heart rate, body temperature, weight, and hydration readings. These measurements were taken by participants twice a day and uploaded from the Bluetooth/WIFI-enabled medical devices installed in the participants' homes [35]. The RTLS study employed unique type of location sensors that were worn on the wrist to track the participants' coordinates for motor behavior analysis. [32]. The Smart Diaper System also utilized sensor-equipped diaper to detect physiological data such as urine flow rates, urine frequencies, and urine outputs, to further predict the occurrence of IAD [22].

Outcomes of UTI Prediction Models and Key Findings: Figure 4 summarizes the outcomes of UTIs prediction models across different studies. Among the seven included studies, six studies reported the outcomes of seven UTI prediction models [32], [33], [34], [35], [36], [37] while one study only reported the outcomes in IAD. The **sensitivities** (recall or true positive rate) of UTI prediction models varied significantly, ranging from 65.2% to 91% (mean sensitivity = 80.6%, SD = 9.4). This variation suggests that while some models are highly effective in identifying UTIs, others need refinement. The **precision** (positive predictive value) of these models also showed substantial variability, from 63.5% to 86% (mean precision = 75.4%, SD = 8.1). These metrics indicate a moderate to high capability of the models to correctly identify true positives, but with room for improvement in reducing false positives. **Specificity,** or the true negative rate, varied from 70.9% to 88%, with a mean specificity of 79.5%. This indicates that the models were generally effective in correctly identifying individuals who did not have UTIs, though there is some variability in performance across different studies. Overall, Li, Rezvani, et al. (2021)'s attention-based, deep learning model and Ramazi et al. (2022)'s deep learning model achieved the highest sensitivity (91%) in UTI prediction, while Li, Kolanko, et al. (2021)'s semi-supervised (DNN+ probabilistic) model attained the highest precision (86%). Both Capstick et al. (2024)'s risk stratified machine learning model and Enshaeifar et al. (2019) 's supervised (NMF & iForest) model achieved the highest specificity (88%) in correctly identifying patients without UTIs. Additional data included a 5.1% alert rate from Bijlani et al. (2022) when their model was evaluated for UTIs and hospitalization. The RTLS program also reported a high sensitivity and high specificity model (sensitivity range = 0.88-0.91; specificity range = 0.71-0.88) for predicting falls, delirium, and UTIs [32]. In contrast, the Smart Diaper System showed a sensitivity of 32.8% in detecting urine voiding. Overall, the UTI prediction models reported in the TIHM and RTLS study outperformed the Smart Diaper System while exhibiting higher sensitivity, specificity, and precision, alongside a low alert rate in UTI predictions.

Discussion

This scoping review identified seven studies exploring digital interventions aimed at managing or preventing UTIs in persons living with dementia and their caregivers. The review's objectives were to categorize the types of digital interventions and devices used and to summarize the outcome variables and key findings regarding UTI prevention and management in this population. Our main findings were as follow. First, only three digital interventions were identified among the seven studies, all of which centered on sensor-based research primarily aimed at detecting occurrences of UTIs. Additionally, 86% (n=6) of the studies incorporated AI algorithms, primarily utilizing sensory data collected via the IoT or sensor devices integrated with AI algorithms. Second, the outcome variables from the three interventions were categorized into two types: environmental data and physiological data. And third, we summarized the outcomes and key findings of seven UTI detection models reported across the studies, comparing them based on their sensitivity, specificity, and precision.

The TIHM for Dementia Care of Care employed a comprehensive array of sensors, including PIR sensors, motion sensors, and pressure sensors, to collect extensive environmental and physiological data. This multi-sensor approach allowed for a robust monitoring system that could identify subtle changes in the participants' health status. On the other hand, the RTLS intervention utilized wrist-worn tags to monitor motor behavior through location tracking. This approach, while more focused, was effective in predicting falls and delirium. The Smart Diaper System, in contrast, used conductor sensor devices within a diaper to measure urine flow and frequency, aiming to detect incontinence-associated dermatitis (IAD) and bed sores, which are conditions that may predispose patients to urinary tract infections (UTIs). The contrast between these methods highlights the trade-off between breadth of data collection and focus on specific health indicators. While the TIHM system provides a wide-ranging overview of various health parameters, the RTLS and Smart Diaper System focus on specific behaviors and conditions, respectively. Future research could explore combining these approaches to enhance overall monitoring accuracy, integrating broad environmental and physiological monitoring with targeted behavioral and condition-specific tracking.

While TIHM, RTLS, and Smart Diaper System employed various technological components such as sensors, conductors, WIFI/Bluetooth devices, and wearable devices, they shared two common features: 1) all interventions incorporated sensor-based technology while 80% of the interventions were incorporated with AI algorithms, and 2) their primary objective was early detection of UTIs in persons living with dementia. The features of sensor-dominant technological interventions observed in our study were unexpected and did not entirely align with existing digital interventions for other populations challenged with UTIs. For instance, Vellinga et al. (2021) developed a smartphone diary app to help users record their UTI symptoms using the concept of an electronic diary. While the app demonstrated an efficient and acceptable means of collecting data on the natural course of UTIs [38], it primarily included symptom tracking without providing UTIs preventive knowledge. The app's primary user base consisted of young women with a mean age of 29.7 (SD 14). Similarly, Le et al. (2021) introduced two digital knowledge translation tools aimed at helping parents of children with urinary tract infections. These tools proved to be useful mediums for sharing health information, with their users having a mean age of approximately 40 (SD 13) [39]. More recently, Pat et al. (2023) developed a telemedicine tool, myRUTIcoach, aimed at providing knowledge on UTI preventive measures. This digital intervention successfully enhanced effectiveness and self-management among its users. However, Pat's intervention primarily targeted women with recurrent UTIs, with a mean age of 57.9 (SD 19). In contrast, our study's sensor-dominant interventions target a different demographic and aim to address the specific needs of persons with dementia and their caregivers. This demographic significantly differs from those in the aforementioned studies, with a mean age of 79.9 (SD 11.2), highlighting the need for tailored digital solutions in this population.

Our findings demonstrated that sensor technology is increasingly employed in predicting diseases and analyzing symptoms. This observation is consistent with several studies on digital interventions that integrate sensors, the IoT, and AI algorithms. For example, in the field of cardiovascular diseases, IoT and

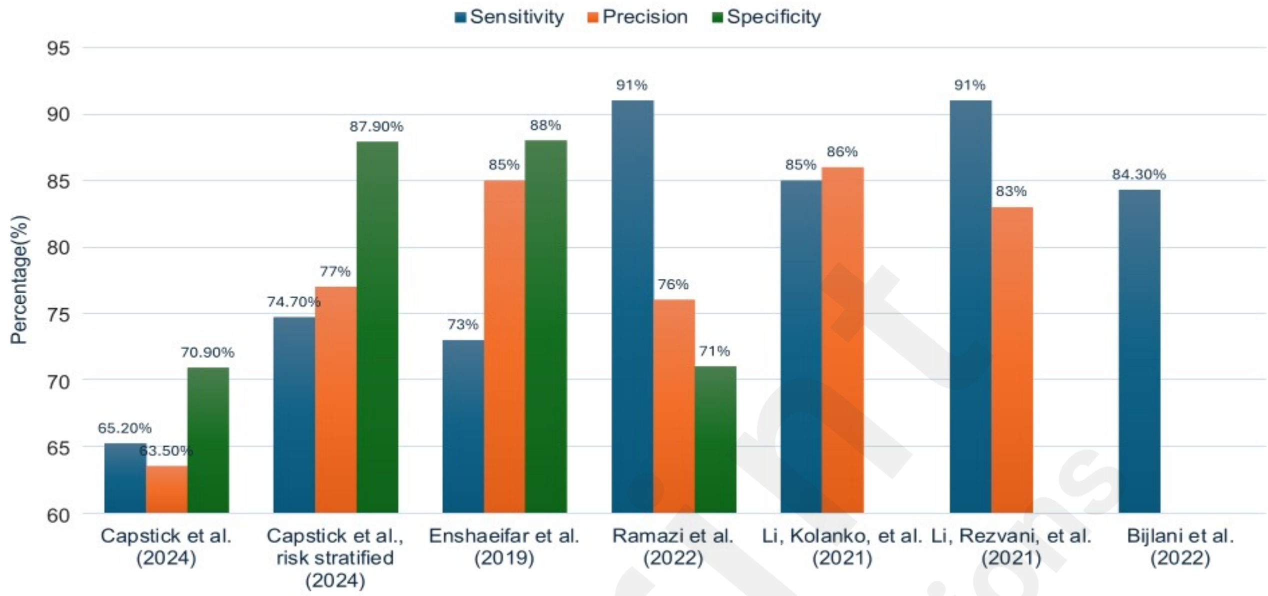
AI have been used to analyze real-time sensor data, helping in the early detection and management of heart conditions [40], [41]. Similar applications are found in the management of diabetes, where continuous monitoring and predictive analytics improve patient outcomes [42], [43], [44]. Additionally, sensor technology is also used in predicting falls, delirium, agitation, and cognitive status in people with dementia [43], [45], [46]. This alignment highlights the growing role of sensor-based interventions in healthcare research.

We reported two types of outcome variables in this review. *Environmental data* refers to information collected from sensor-based systems, smart home devices, or IoT technologies; this includes data from various sensor devices such as infra-red (PIR) sensors, motion sensors, location sensors, pressure sensors, door sensors, smart plugs, and central energy consumption monitoring devices [32], [33], [34], [35], [36], [37]. *Physiological data* encompasses measurable biological information that reflects the functioning of the body's systems, collected via wearable, Bluetooth, or WiFi-enabled medical devices, or current flow sensor device. Common physiological data include blood pressure, heart rate, body temperature, weight, hydration readings, urine volume, and frequency [22], [32], [33], [34], [35], [36], [37]. The integration of these types of data in digital interventions for UTIs detection and management is significant. Environmental data, such as activity patterns and motor behaviors, can provide early indicators of health issues, including UTIs, by highlighting deviations from normal behavior [47], [48]. Physiological data offers direct measures of the body's response to potential infections, such as changes in vital signs or urine characteristics, which are crucial for timely and accurate diagnosis [7]. These findings feature the potential of digital interventions in enhancing UTIs screening and monitoring in demented populations.

Finally, seven UTI prediction models were collated over the six studies (Figure 3) in regard to their sensitivity, specificity, and precision of UTI detection. In studies regarding TIHM and RTLS interventions, the UTI prediction models demonstrated average levels of 80.6% sensitivity, 79.5% specificity, and 75.4% precision. These interventions provided practical digital solutions for: 1) effective early detection of UTIs events with minimized the false alarm and higher accuracy; 2) and identification of changes in daily activity patterns in persons living with dementia; 3) alerting clinicians and caregivers and enhanced screening when considering treatment. A retrospective study developed an early warning model for UTIs in patients with neurogenic lower urinary tract dysfunction, demonstrating good discrimination ability and consistency, with lower sensitivity (62.5%), but higher specificity (100%), and accuracy (90%) [49]. Another literature review published in 2022 summarized the use of AI algorithms in UTI diagnosis among all age groups, providing an overview of various AI models in UTI diagnostics [50]. The average sensitivity and specificity reported in their study were 84.2% and 82.6%, respectively. Although both studies presented slightly higher specificity, sensitivity, and accuracy in their UTI detection models, they relied on clinical data and biomarkers, which are more intrusive and require clinical settings with healthcare provider involvement. In contrast, our included studies utilize home-setting, non-intrusive sensor technology which might be able to provide safe and effective care for persons with dementia and their caregivers.

Figure 3. Outcomes of UTI prediction models across studies. This bar chart presents the sensitivity, precision, and specificity percentages reported in included studies in this review. These studies evaluated different AI models or algorithms for the clinical prediction of urinary tract infection (UTI) occurrence, emphasizing their performance metrics.

Figure 3. Outcomes of UTI Prediction Models Across Studies



Limitations in Study characteristics and Research Biases

The inclusion of a limited number of studies highlights several gaps and limitations in this review. As presented in the results and depicted in Figure 2, all the included studies were observational, focusing on persons living with dementia. Furthermore, 72% of these studies were home-based and conducted in the United Kingdom. The **small number of studies** included in this review (less than 10) significantly restricts the ability to draw comprehensive and generalizable conclusions. This limited sample size points to a need for more research in this area to establish a robust evidence base. The **predominance of observational studies** poses a limitation in terms of the strength of evidence. This finding aligns with a systematic review published in 2019, which evaluated the current state of home-based digital biomarker technologies for monitoring cognitive functions in individuals with cognitive impairment and Alzheimer's disease [51]. That review similarly noted that all 26 included studies were observational and took place at home with community-dwelling older adults. Observational studies can indicate associations but are less capable of establishing causality due to potential confounding factors [52]. This reliance on observational data underscores the necessity for more rigorous study designs, such as randomized controlled trials (RCTs), which can provide stronger causal inferences in UTI prevention and management [52]. Conducting RCTs in this domain would offer more definitive guidance on strategies for preventing UTIs and managing dementia-related challenges, thereby benefiting both persons with dementia and their caregivers. Moreover, with 72% of the studies conducted in the United Kingdom, there is a clear **geographical bias**. This regional concentration limits the generalizability of the findings to other countries with different healthcare systems, cultural contexts, and population demographics. Future research should aim for a more geographically diverse sample to ensure the findings are applicable across various settings. These settings might include clinical environments such as hospitals and clinics, in-home settings where patients receive care within their own residences, and long-term care facilities such as nursing homes and assisted living communities. By including participants from these varied contexts, research can better account for the different challenges, resources, and patient needs that each setting presents, ultimately leading to more comprehensive and universally applicable findings.

The gender ratio of the participant population reveals another important bias. Specifically, the studies included a total of 230 males (52.2%) and 211 females (47.8%); with one of the studies only recruited male participants. Despite this, it is well-documented that women are more commonly affected by both dementia and UTIs than men [53]. For instance, almost two-thirds of Americans with Alzheimer's are women [54]. Similarly, in the United Kingdom, 65% of the people living with dementia are women [55] and for patients older than 70 years old, women have a 1.5 times higher chance of developing UTIs compared to men [56]. The overrepresentation of males in our study samples introduces a **population bias**, suggesting that the findings may not be fully representative of the broader population, particularly females. Addressing this bias in future research is crucial to developing interventions that are effective across all gender groups. Moreover, it is essential to consider the perspectives and health needs of LGBTQ+ individuals, who often face unique healthcare challenges and disparities. Research has shown that LGBTQ+ populations may experience higher rates of certain health conditions, including mental health issues, which can intersect with conditions like dementia [57]. Furthermore, transgender individuals, in particular, may encounter barriers to healthcare and may have different experiences with conditions such as UTIs due to anatomical differences and hormone therapies [58]. Including a diverse range of gender identities and sexual orientations in future studies will help ensure that findings and interventions are inclusive and applicable to the entire population, thereby enhancing the equity and effectiveness of healthcare solutions.

From a Clinical Perspective

We want to highlight two critical points from the lens of clinical care. Firstly, there is a lack of theoretical foundations of the included studies and interventions. The digital interventions in this study were solely designed with the concept of detections and predictions of the UTIs diagnosis rather than offering prevention strategies for their users. The interventions were not informed with theory, framework, or follow the UTIs protocol or guideline such as Infectious Diseases Society of America (IDSA) or European Association of Urology (EAU). While sensor-based technology plays a crucial role in the early detection and management of UTIs, offering continuous, real-time data collection for timely identification of risk factors and early signs of UTIs [37], [42], its strength lies primarily in diagnosis. However, sensor-based interventions fall short in delivering comprehensive strategies to resolve the underlying risk factors and shift outcomes in UTIs. Additionally, it lacks mechanisms to actively alleviate UTIs symptoms or promote healthy behaviors to prevent the onset of the disease. Thus, while the technology excels in diagnosis, it lacks the essential elements required for a holistic approach to UTIs management and prevention. Interventions that encompass behavioral change theory, UTIs framework, or protocols, such as educational content on hygiene practices [18], lifestyle modifications, and behavioral interventions [59], [60], are crucial for mitigating UTIs risk factors and promoting overall urinary health in persons with dementia. For example, education campaigns can raise awareness about the importance of hydration, proper hygiene practices, and timely voiding habits, which can significantly reduce the likelihood of UTIs occurrence [7], [11].

Secondly, caregiver involvement as users in digital interventions can significantly aid in reducing UTI occurrence in persons with dementia. Persons living with dementia often struggle with maintaining proper hygiene, recognizing the need to hydrate, and remembering to void regularly, which are critical factors in preventing UTIs [7], [11]. Digital interventions that include caregivers as active participants can provide timely reminders and instructions for these essential activities, ensuring consistent adherence to preventive measures [45]. Caregivers can improve the effective use of technology [17], [59] such as monitoring and interpreting health data collected by digital tools, such as fluid intake and voiding patterns, enabling them to promptly address any irregularities. Furthermore, caregivers can implement recommended hygiene practices and make necessary lifestyle adjustments based on the insights provided by digital interventions [61]. By integrating caregiver support into digital health solutions, the management of UTIs in persons with dementia becomes more proactive and personalized, ultimately reducing the frequency and severity of infections.

Conclusions

This scoping review explored current digital interventions for managing and preventing UTIs in persons with dementia and their caregivers. Our principal findings revealed three key aspects: the predominance of sensor-based interventions, the categorization of outcome variables into environmental and physiological data, and the comparative analysis of UTI detection models. Despite the promise shown by these digital interventions, the review identified significant gaps and limitations, including a small number of studies, observational study designs, geographical biases, and an overrepresentation of male participants.

Digital interventions in this review primarily employed sensor-based technology integrated with AI algorithms, with a focus on early UTI detection. Nevertheless, these interventions were deficient in theoretical underpinnings and preventive strategies. This highlights the necessity for comprehensive interventions that not only identify but also prevent UTIs, necessitating more active involvement of caregivers to enhance compliance with preventive measures. Future research should broaden its scope to encompass diverse geographical locations and demographics, ensuring the generalizability of findings and strengthening causal inferences through RCTs. Incorporating preventive strategies into digital interventions grounded in clinical guidelines and behavioral change theories can enhance UTI management for persons with dementia, offering comprehensive education on hygiene practices, lifestyle modifications, and proactive behavioral interventions. Active involvement of caregivers in these interventions, supported by training programs and access to real-time monitoring capabilities, can alleviate the burden on caregivers and improve their effectiveness in managing UTIs. By leveraging advanced technologies such as AI and IoT integration, continuous monitoring and early detection of UTI symptoms can be facilitated, leading to timely interventions and improved health outcomes in both persons living with dementia and their caregivers. These developments hold promise for enhancing healthcare system efficiency and improving the quality of life for persons living with dementia and their caregivers while reducing healthcare costs associated with UTI management.

Conflicts of Interest

None declared.

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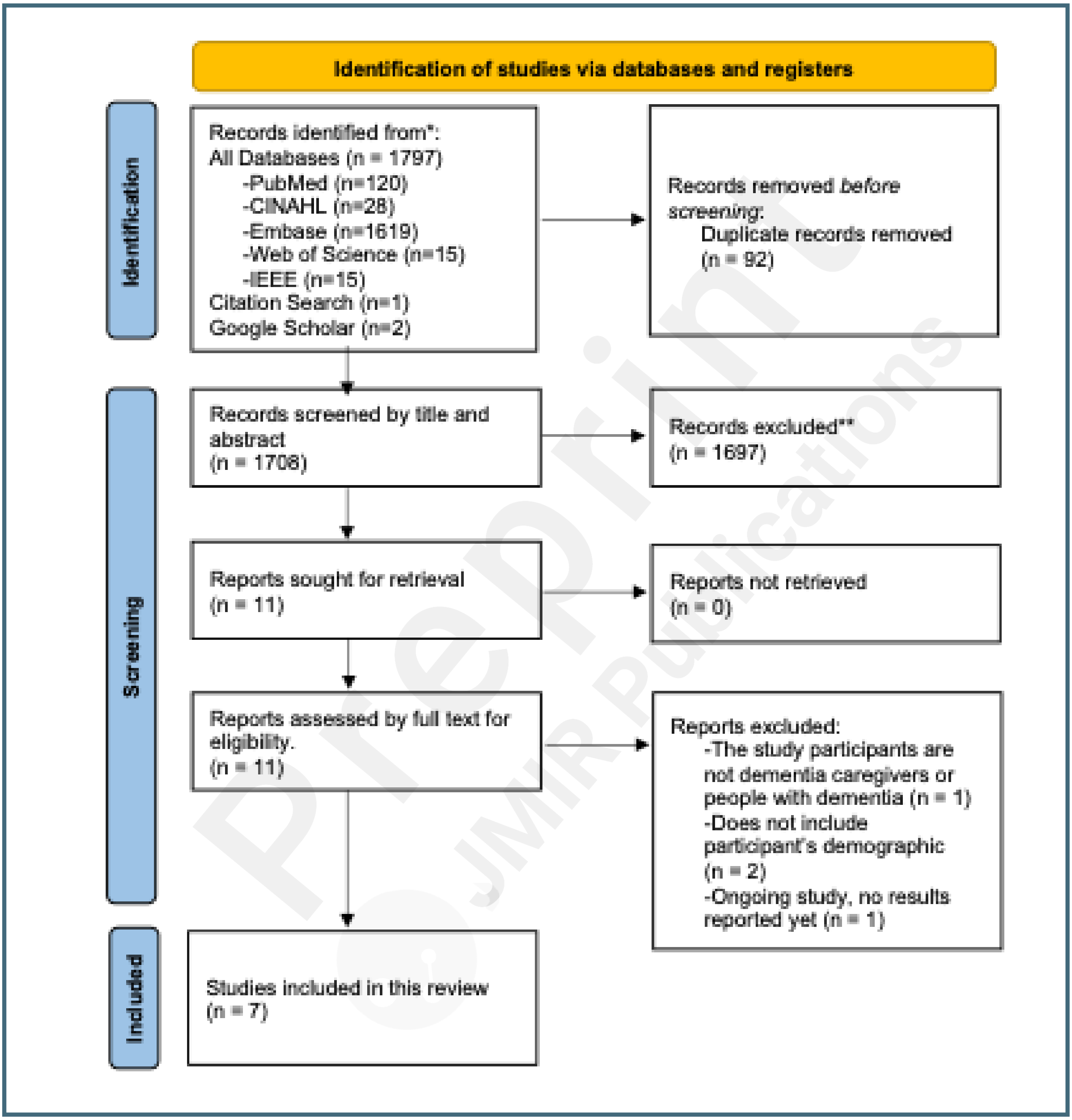
25

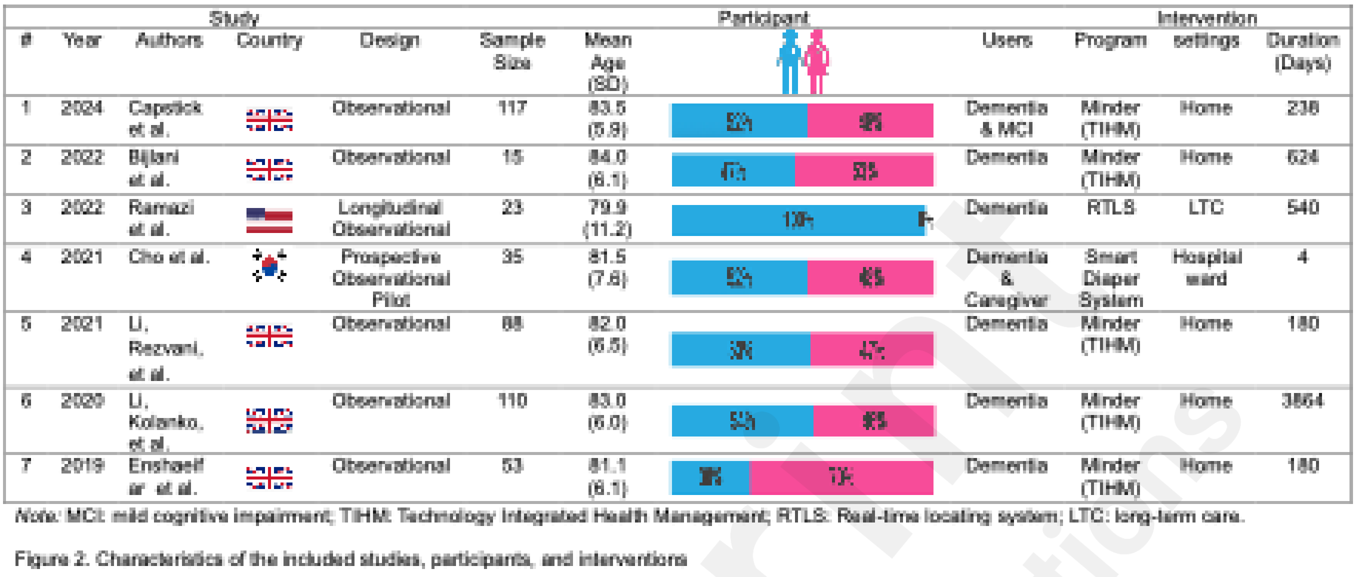
Supplementary Files

Figures

Prisma-ScR flow chart. The PRISMA-Scr (Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews) flow chart describes the process of selecting studies for inclusion in this scoping review.



Characteristics of the included studies, participants, and intervention. The figure provides detailed information for each study, including the sample characteristics of the participants and the intervention details.

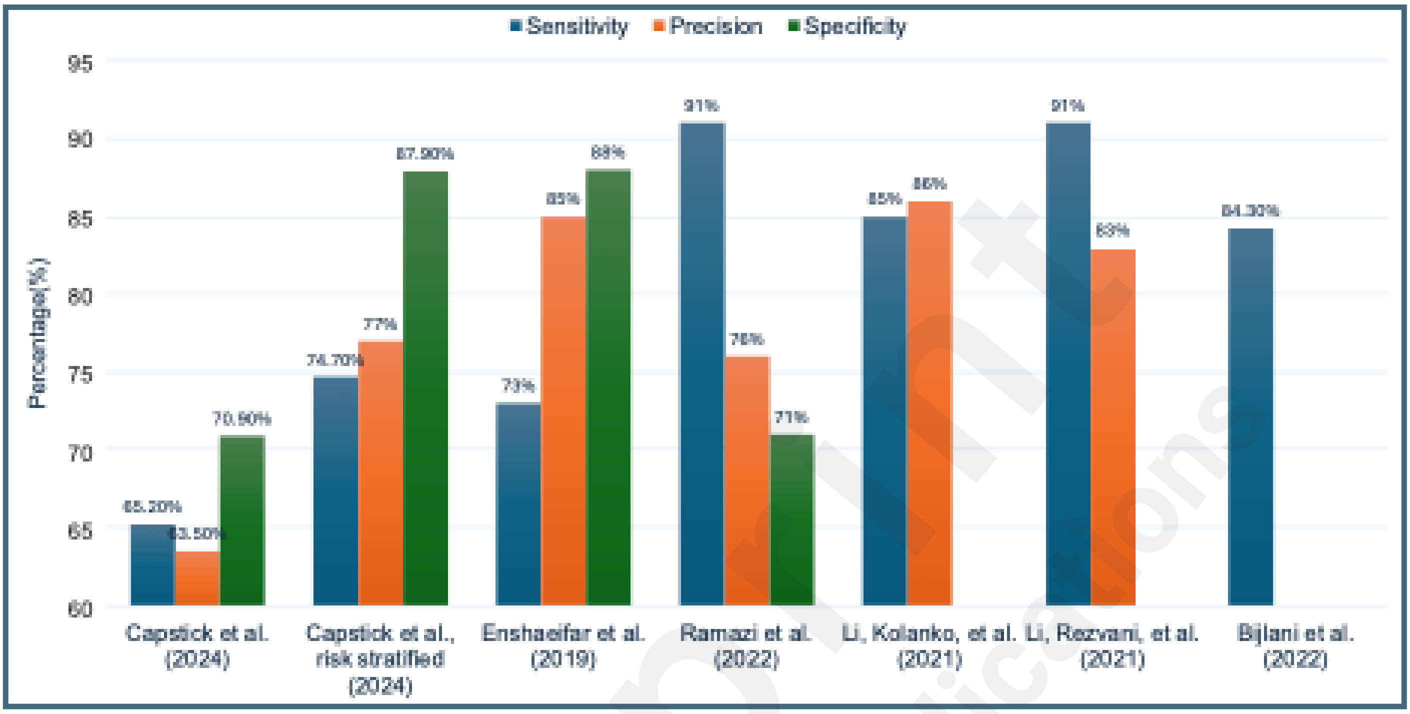


Study						Participant		Intervention			
#	Year	Authors	Country	Design	Sample Size	Mean Age (SD)		Users	Program	settings	Duration (Days)
1	2024	Capstick et al.		Observational	117	83.5 (5.8)	52% / 48%	Dementia & MCI	Minder (TIHM)	Home	238
2	2022	Bijlani et al.		Observational	15	84.0 (6.1)	47% / 53%	Dementia	Minder (TIHM)	Home	624
3	2022	Ramazi et al.		Longitudinal Observational	23	79.9 (11.2)	100% / 0%	Dementia	RTLS	LTC	540
4	2021	Cho et al.		Prospective Observational Pilot	35	81.5 (7.6)	54% / 46%	Dementia & Caregiver	Smart Diaper System	Hospital ward	4
5	2021	Li, Rezvani, et al.		Observational	88	82.0 (6.5)	53% / 47%	Dementia	Minder (TIHM)	Home	180
6	2020	Li, Kolanko, et al.		Observational	110	83.0 (6.0)	54% / 46%	Dementia	Minder (TIHM)	Home	3864
7	2019	Enshaeifar et al.		Observational	53	81.1 (6.1)	29% / 71%	Dementia	Minder (TIHM)	Home	180

Note: MCI: mild cognitive impairment; TIHM: Technology Integrated Health Management; RTLS: Real-time locating system; LTC: long-term care.

Figure 2. Characteristics of the included studies, participants, and interventions

Outcomes of UTI prediction models across studies. This bar chart presents the sensitivity, precision, and specificity percentages reported in included studies in this review. These studies evaluated different AI models or algorithms for the clinical prediction of urinary tract infection (UTI) occurrence, emphasizing their performance metrics.



CONSORT (or other) checklists

PRISMA checklist.
URL: http://asset.jmir.pub/assets/ec2d2d046cb5860677d9b6d74af989cf.pdf