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Voice-Based Notification of Care Workers' Arrival Time: Concept, Implementation and Validation in a Pilot Study

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Abstract

Due to population aging, the need for home care has increased. This leads not only to staff shortages, but also to planning challenges for care organizations. Rescheduling home visits places a strain on everyone involved in care provision. Above all, it is a difficulty for care-service users and their relatives that the only way of getting information about changes in care visits is to call the care organization. These additional phonecalls add to the stress of care workers. This paper presents an ICT service that allows home-care service users to request the arrival time for a care worker's next visit using a voice-based approach. The voice-supported service, 'notification of care workers' arrival time', uses two-stage data processing to predict the time of the visit the closer it gets. In the first step, staff-scheduling data is used; in the second step, the data is enriched with the individual care worker's current movement data. This approach was tested in a pilot in 2021 and validated using data for 174 care-service users and 26 care workers. Improvements for future research are suggested.

Keywords:

spatio-temporal data mining, home care, ambient assisted living, voice assistant, AAL

1 Introduction

Many European countries take account of older people's preference to stay at home as long as possible (Ahn, Kwon, & Kang, 2020; Vasunilashorn, Steinman, Liebig, & Pynoos, 2012; Wagnild, 2001) by giving priority to care at home over residential care (Spasova et al., 2018). This leads to challenges not only in care resources (Gesundheit Österreich GmbH, 2019; Strandell, 2020), but also in care organizations' route planning and scheduling of care workers (Cissé et al., 2017; Fikar & Hirsch, 2017; Grieco, Utley, & Crowe, 2021). Visit scheduling for care workers follows national regulations (e.g. compliance with rest periods) and is not usually set in stone, as changes in, for example, the health of care-service users and/or care workers

often require the rescheduling of visits at short notice. Changes may also result from visits that take longer due to emergencies, or simply traffic jams (Fikar & Hirsch, 2017).

This rescheduling of care visits, which takes place repeatedly, puts a strain on everyone involved. Care workers are exposed to permanent stress to complete their visits in time and make up for a delay due to traffic congestion (Trukeschitz, Kieninger, Ebner, & Schneider, 2020). Similarly, care organizations' service centre staff face challenges in dealing with a growing number of phonecalls from customers requesting updates on the time of their visit. Most importantly, unannounced changes in care visits pose challenges for home-care service users and their informal carers in planning their day, which in turn leads to stress and dissatisfaction. All these problems are caused by insufficient information and – given the number of requests – out-dated technology for managing/obtaining accurate information.

This paper provides technical details for a newly developed service for a voice assistant which allows home-care service users to request the arrival time of their care workers using their voice only. We focus on the implementation of this 'notification' service and the results of the pilot. We present a two-stage data processing approach that uses staff-scheduling and GPS data; the approach allows for more accurate time predictions the closer a visit gets. The analysis of the GPS data only relies on the stationary part of the GPS trajectory, which will allow future solutions to better comply with data protection regulations.

The paper is organized as follows: Section 2 deals with the concept, the requirements concerning three countries (Austria, Switzerland and Belgium), and the implementation of the notification service using a voice assistant. Details of the pilots carried out in Austria and Switzerland can be found in Section 3, and the results in Section 4. The paper closes with a discussion and conclusions drawn from the results (Section 5).

2 Notification of arrival time using a voice assistant

2.1 Idea and concept

The 'notification of care workers' arrival time' service is designed to provide information on the time span in which a care worker is expected to visit her/his service-user. This information should be provided in a form suitable for older people. A voice assistant developed especially for older people was used, as speech is the most natural form of human communication (Akçay & Oğuz, 2020). The concept behind the tool is that the predicted arrival time becomes increasingly accurate the closer the visit gets thanks to two-stage data processing, with 'low accuracy' and 'medium accuracy' (Figure 1).

Low accuracy: For visits scheduled more than one day and less than seven days in the future, the planning data (the worker's weekly rota) is used for the forecast. Planning data is also used for visits on the same day when GPS data is not available (e.g. the care worker has not yet started work).

Medium accuracy: For visits on the same day, care workers' real-time movement data (GPS data) is also used for more accurate predictions.

The trigger for the service is the same, regardless of the processing/accuracy level. This is the service-user calling 'Hello CARU! Arrival!'.

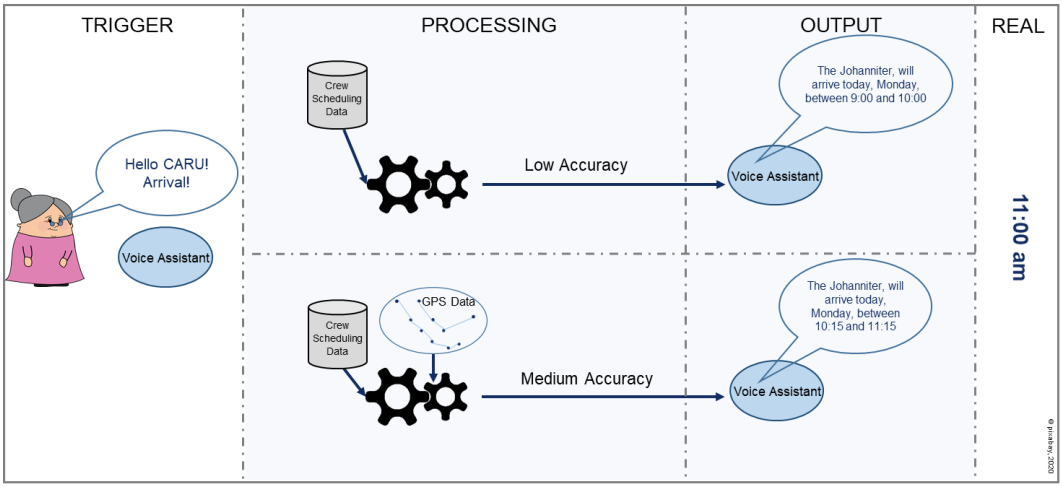

Figure 1: Concept of the notification of arrival time service using a voice assistant (source: own representation)

2.2 Requirements

The requirements for the service were collected in co-creation workshops with care workers and service staff in the participating countries – Austria, Switzerland and Belgium (Trukeschitz et al., 2020). The input of the Johanniter, a humanitarian/ social care organization, was also considered. Due to the first COVID-19 wave in 2020, the planned workshops with care-dependent people could not be held. Their contribution to the development was therefore in the form of information provided by the care organizations.

During the co-creation workshops, four main requirements were identified (Trukeschitz et al., 2020): (i) the notification of care workers' arrival time must be generated automatically (no extra work/pressure for care and service staff); (ii) the arrival-time prediction needs to be accurate to within a certain range (60 minutes was suggested, i.e. 30 minutes either side of the projected time); (iii) a suitable time for the arrival-time prediction to be notified should be considered so that care workers do not feel stressed, and (iv) the notification should include the date and the day of the week.

It was important to Johanniter's management that their organization did not have access to the care workers' movement data (GPS data), and that only the research partners should have such access, in order to protect their workers' privacy. In this particular case, it was agreed that the data would be processed and analysed on designated servers of the research partner (University of Applied Sciences Wiener Neustadt).

2.3 Implementation

In order to implement the concept, including the requirements, data sources were needed, a system that maps the corresponding workflow had to be designed, and how to calculate the arrival time had to be devised.

Data sources

To realize the first 'low accuracy' stage of the two-stage data processing, **staff-scheduling data** was needed. This data was provided via an interface (web service) from the planning and scheduling system of the end-user organizations, and represented the starting point for the prediction of the arrival time. The following data was processed via the web service for a defined period (`periodFromDate, periodToDate`): `visitId, clientId, clientAddress, employeeId, visitFromTimestamp` and `visitToTimestamp`.

Another source was **GPS data**, used for the second level, 'medium accuracy'. The original plan was to use company smartphones to record the GPS data. However, during the technical clarification, it was realized that not all employees in all end-user organizations have such a device, and one organization blocks additional apps on company smartphones. Therefore, it was decided to use GPS trackers for data collection. Requirements for the trackers were that they should be small, lightweight, waterproof and allow data transmission. They should also offer the option of setting different recording intervals. Seven trackers that met these criteria (Figure 2) were identified during an internet search in 2019. After an initial internal test, two of them were tested further with five care workers over 28 days, following which the Queclink GL300MG was chosen.

1	2	3	4	5	6	7
Teltonika		Meitrack	Tk-Star		Concox	Queclink
GH5200	TMT250	P99L	209A	209B	Qbit	GL300MG

Figure 2: GPS trackers (source: own representation)

System architecture and workflow

The system architecture of the notification service was designed to process the two data sources (staff-scheduling and GPS data) required to calculate the arrival time (for details, see Section 0) and to pass on the results to the voice assistant. The results could only be accessed by the registered service-user's voice assistant. The project partner responsible for the voice assistant required the third-party communication service Twilio for voice and text processing (speech-to-text and text-to-speech). The service for calculating the arrival time consisted of seven main components (Figure 3): (i) the *Twilio Backend* for interaction with the Twilio service;

(ii) the *Prediction Backend* to calculate the arrival time; (iii) the *GPS Data Server* for continuously processing incoming GPS data from the care workers; (iv) the *Stay Point Detection* component, which continuously calculates new stay points (places where the worker remains for some time) based on GPS data from care workers; (v) the *Web Data Sync Backend* to process and synchronize staff-scheduling data, and (vi & vii) *GeoJSON DB-Export* and *Leaflet Viewer* for monitoring the system and its functionality.

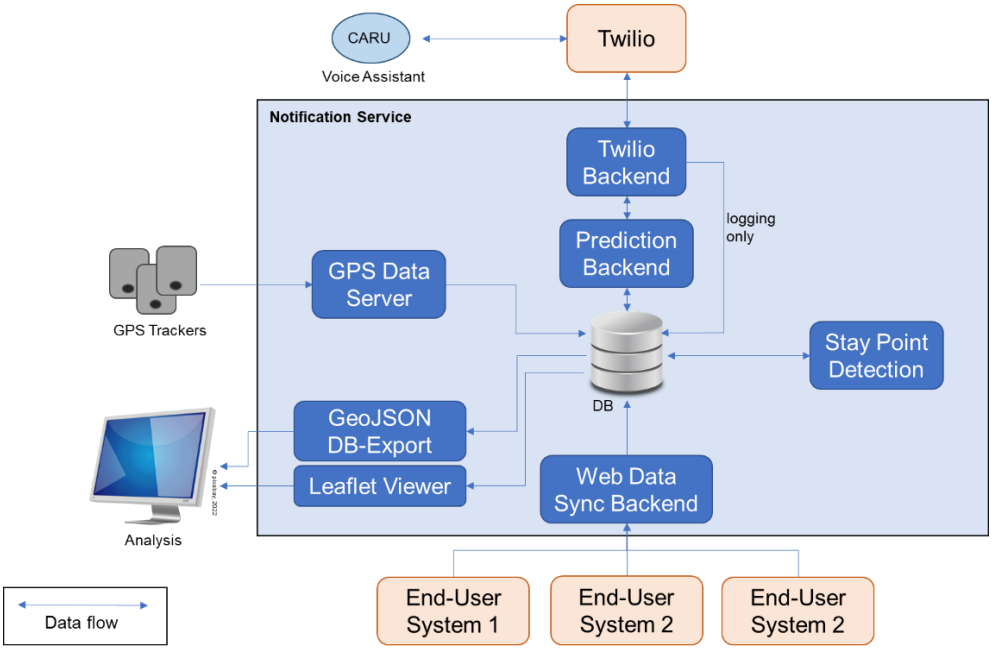

Figure 3: System architecture of the notification service (source: own representation)

This architecture enabled the implementation of the workflow shown in Figure 4. In the first step, the care-service user calls 'Hello CARU! Arrival!'. Then the CARU device calls the Twilio service, which in turn calls the notification service. The notification service calculates the arrival time and returns the result to Twilio, which sends the voice output to the end-user's CARU device. After discussions with end-user organizations, the notification included the day of the week and concepts of time, such as today, tomorrow, the day after tomorrow, or this week, instead of the date.

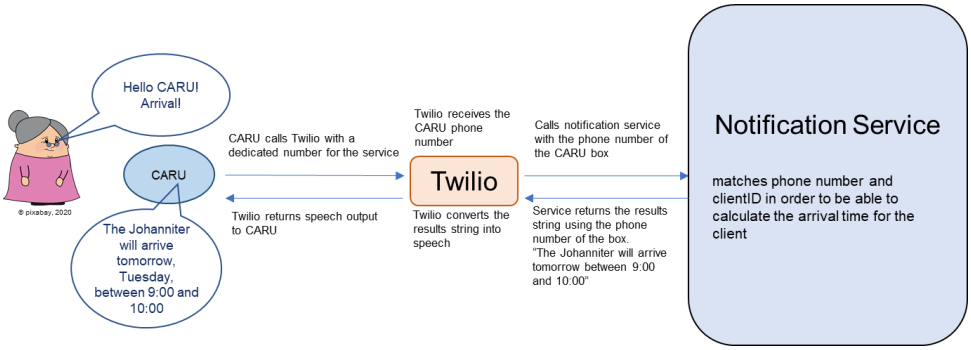

Figure 4: Workflow of the notification service for home care (source: own representation)

Arrival time calculation

The arrival time was calculated using both staff-scheduling data and GPS data. With regard to a future product, permanent GPS monitoring would lead to data protection issues. Therefore, the idea was to monitor only the stationary parts of a GPS trajectory – i.e. visits by a care worker to a service-user's home (so-called 'stay points'). In the future, as soon as a stay point has been identified, it will be possible to delete the data for the mobile parts of the care worker's trajectory that immediately precede the stay point. A stay point is identified by `latitude, longitude,` t_{in}, t_{out}. The start of a stay point is marked with t_{in} and the end with t_{out} (Liu & Seah, 2015). Stay points are generated using clustering approaches (Schneider, Gröchenig, Venek, Leitner, & Reich, 2017), which make it possible to detect (finished) visits and thus, in combination with staff-scheduling data, to determine deviations in subsequent visits.

The arrival time was calculated in three stages: (i) time-based/incremental clustering to generate stay points; (ii) assignment of stay points to visits based on staff-scheduling data; (iii) calculation of arrival time deviations for making predictions. The following components of the system architecture (Figure 3) are involved: *Web Data Sync Backend*, *GPS Data Server*, *Stay Point Detection* and *Prediction Backend*.

Time-based/incremental clustering to generate stay points

An adapted version of a mixed-method approach introduced by Ye et al. (2009) was used to generate stay points. This approach normally has two stages. In the first, a trajectory is processed and stay points are generated. In the second, new and existing stay points are merged using density-based clustering. Since in this project stay points had to be determined as they occurred, only stage one of the approach was used and adapted. Figuer 5 shows the pseudocode of the algorithm to extract stay points from GPS data. A stay point was created when a care worker spent more than the `minTime` within a range of `maxDistance`. Distances were calculated using Euclidean distance. Incoming stay points have an `inTime` (start) and a `center` point (the average position of all GPS points in that cluster); the end of a stay time is marked by an `outTime`.

```
Stay Point Clustering
function toStayPoints(points, maxDistance, minTime)

INPUT>   points      : [GpsPoint]
         maxDistance : Distance
         minTime     : TimeSpan
OUTPUT>  staypoints  : [StayPoint]
PRECOND> points are sorted ascending by time

if isEmpty(points) then return []

(first, next)   := split(points)
(cluster, rest) := next.TakeWhile
  (λp -> euclid(first.point, p.point) ≤ maxDistance)

if isEmpty(cluster) then
  return toStaypoints(next, maxDistance, minTime)

lastPoint   := last(cluster)
clusterTime := lastPoint.time - first.time

if clusterTime < minTime then
  return toStaypoints(rest, maxDistance, minTime)

inTime  := first.time
outTime := isEmpty(rest) ? None : lastPoint.time
center  := cluster.average(λp -> p.point)
return new StayPoint(inTime, outTime, center)
         :: toStayPoints(rest, maxDistance, minTime)
```

Figure 5: Pseudocode of stay point clustering for the notification service (source: own representation)

Assignment of stay points to visits based on staff-scheduling data

Stay points cannot automatically be classified as visits, as they can also be caused by traffic jams or lunch breaks. Therefore, in this step, the stay points were matched with the visits from the staff-scheduling data. Scheduled visits and stay points were compared in terms of space and time. The address of the visit provides the spatial component. The start and end times of the planned visit provide the temporal component. If the time difference between a stay point and a visit is less than a predefined time and distance, a match is generated.

Calculation of arrival time deviations for making predictions

In this last step, the arrival time deviation was calculated based on the matches identified. For the calculation, the most recent match was always used, since it cumulatively contains all previous deviations (provided that the order of the scheduled visits is kept). If a match was found, the time difference between the matched visit and the stay point was returned and used for predicting the arrival time for subsequent visits. There were two different ways of calculating the time difference, according to whether stay point t_{out} was available or not (i.e. a visit to a previously scheduled client was still ongoing). If a stay point had a t_{out}, the difference between scheduled t_{out} and stay point t_{out} was used for the calculation. Otherwise, the difference between scheduled t_{in} and stay point t_{in} was used.

There is one more peculiarity concerning the matches. It can happen that several stay points are generated for a single visit due to GPS inaccuracies. Of these stay points, the stay point with the earliest t_{in} and the one with the latest t_{out} were used for the calculation. The

calculated differences were then considered when predicting the next visits. If no matches were found or the next visit was not scheduled for that particular day, the next visit according to the staff-scheduling data was returned as the result.

3 Piloting the service

The pilot for testing the notification of arrival time service using a voice assistant was aimed at two target groups: (i) older people who use home-care services or live in assisted living facilities, and (ii) care workers from care organizations. Johanniter (Austria) and Bonacasa (Switzerland) planned to recruit 2 x 25 older people living in home care and assisted living environments, and 2 x 8 care workers based on certain inclusion and exclusion criteria (Trukeschitz et al., 2021). Belgium was not involved in this pilot; the system will be tested there later in the project.

3.1 Settings

Home care setting: in Austria, the notification service was tested with older people using home-care services provided by Johanniter in Innsbruck. Service-users in this setting were visited several times a week, at **varying times**.

Assisted living facilities: in Switzerland, the notification service was tested in smart/**assisted living environments** where people did not have care needs. For these service-users, a concierge is available on site at **fixed times**.

3.2 Equipment with GPS tracker and configuration

Since the Swiss setting did not concern home care but assisted living environments with fixed service times, only the Austrian care workers were equipped with GPS trackers.

The Queclink GL300MGs were equipped with SIM cards for data transmission. The recording interval of the GPS tracker was set to 10 seconds and the transmission interval to 60 seconds, as determined during the pre-test (see "Data sources").

3.3 Parameterization of the arrival time calculation

GPS points were analysed every five minutes and stay points were calculated. A stay point was generated when a care worker remained within a 100-metre radius for more than five minutes (shorter stays were therefore not considered). A stay point was assigned to a visit if it was no more than 250 metres and 6 hours away from a scheduled visit. 6 hours was chosen because care workers frequently swapped scheduled visits, and this was the only way to match stay points appropriately. New arrival times were calculated if a service-user called the notification service, and additionally every 15 minutes to obtain data for further evaluation purposes.

3.4 Measures

Three measures were used for the validation of the notification service: (i) actual use of the service (each call to the notification service registered through the *Twilio Backend* was counted as one use by one person); (ii) scheduled visits (visits as planned by the care organizations); (iii) actual visits made (documented electronically in the care management system by care workers during/after the visit).

3.5 Ethical approval

The pilot (including the informed consents) was reviewed and approved by the independent ethics board of the University of Applied Sciences Wiener Neustadt (11/2019; chairperson: Nimmerichter Alfred).

4 Results

The pilot took place between 15 April and 15 July 2021 and lasted a total of 91 days. In order to make forecasts via GPS, it was necessary for the entire Johanniter care team (26 people) to carry GPS trackers.

For the validation of the arrival time, the data of planned visits for 174 care-service users in Austria were used. For the assessment of the voice assistant, a total of 24 older people participated in the pilot, in Switzerland (17 users; male: 9; female: 8) and Austria (7 users; male: 1; female: 6). The number of care-service users recruited was significantly lower than hoped or planned. However, this is not relevant for the validation of the notification service, as for this purpose data is available for 26 care workers and visits to 174 care-service users, and the calculation did not depend solely on a call being made by the service-users (3.3). A few measures, such as phonecall reduction, cannot be calculated due to the low case numbers. However, these are not the focus of this work. Details of the sample description can be found in Ebner et al. (2021).

4.1 Use of the notification service by care-service users in Austria

Seven home-care users in Austria accessed the notification service 566 times during the test period, or on average of 81 times (median 43) over the test period. Table 1 shows that three out of the seven users called the notification service at least 105 times each within the test period. The usage of the other users ranges between 12 and 43 in the same period. May was the month with the highest usage, followed by April (only half a month) and June (Figure 6).

Table 1: Usage per user and month – Austria (A1 to A7 means client 1 to client 7)

	A1	A2	A3	A4	A5	A6	A7	Total
April	4	36	35	16		5	5	101
May	6	59	81	48	16	17	14	241
June	2	62	53	27	2	20	4	170
July		28	11	14		1		54
Total	12	185	180	105	18	43	23	566

Source: CARU-FHWN-2021

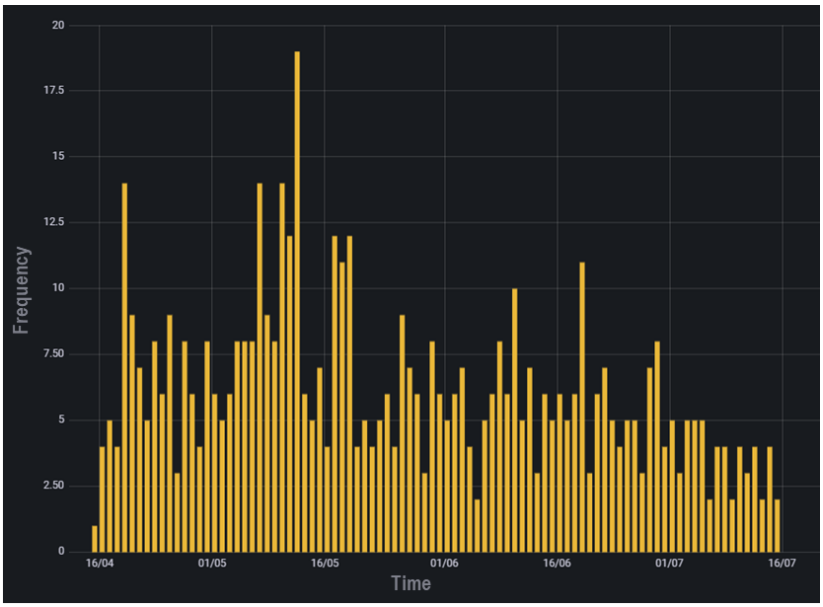

Figure 6: Use of the notification service by care-service users (n = 7) in Austria (source: own representation)

4.2 Use of the notification service by service-users in Switzerland

The 17 participants in Switzerland used the notification service a total of 181 times during the test period. Table 2 shows that five participants used the notification service between 19 and 38 times each within this period. The usage of the others ranged between one and six times. Considering that the test period included only half of April, this was the month with the highest-density usage (Figure 7).

Table 1: Usage per user and month – Switzerland (B1 to B17 means client 1 to client 17)

	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11	B12	B13	B14	B15	B16	B17	Total
April	1	1		3			4	9	2		4	8	1	1	1	16		51
May	1	3	3	1	4	17	2	8	1	3	13	2		2	3	11	3	77
June			2			2		10			2	11		2	2	11	2	44
July								6	3									9
Total	2	4	5	4	4	19	6	33	6	3	19	21	1	5	6	38	5	181

Source: CARU-FHWN-2021

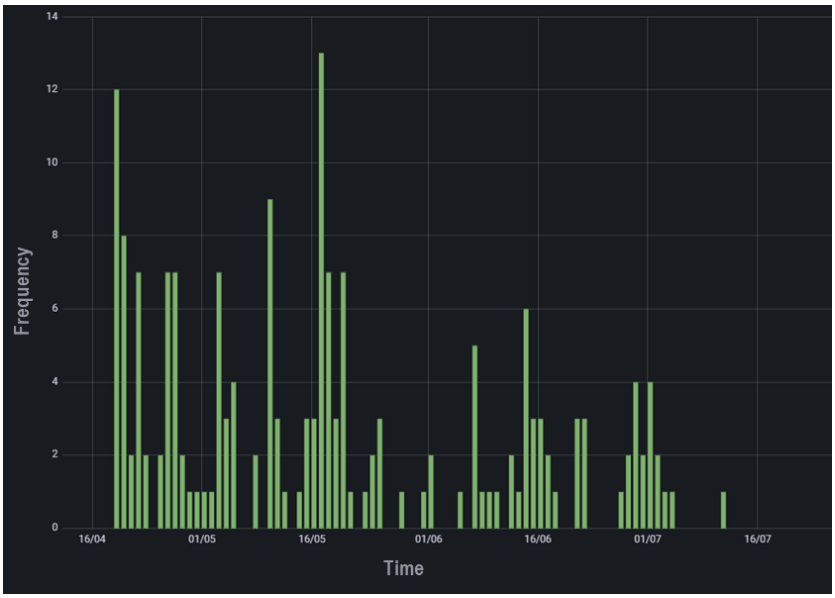

Figure 7: Use of the notification service by service users (n = 17) in Switzerland (source: own representation)

4.3 Validation of the arrival time calculation

Dynamically changing visit times were only relevant in Austria, due to the setting. Therefore, deviations for the current day were only calculated for Austria. In Switzerland, the scheduled times were used by default. The validation therefore used only Austrian data.

We received 13,993,764 GPS points from the 26 care workers visiting 174 care-service users (Table 3) in Austria during the test period. On average, this was 153,777 GPS points per day. Figure 8 shows that data collection varied during the test period. On the first day of the test, over 160,000 GPS points were generated. The following days saw a decline; a few days later, the number of GPS points per day levelled off at 145,000, rising to 185,000 in mid-June. In the last month of the test, fewer and fewer points were received. A comparison of scheduled and actual visits with available movement data shows that GPS trackers were not always carried. Since the trackers transmitted data from the headquarters, it can be assumed that they had been forgotten there.

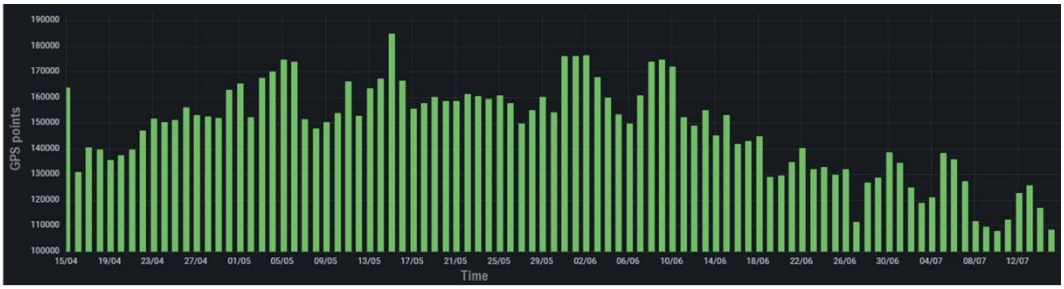

Figure 8: GPS points collected over time (source: own representation)

During the test period, a total of 9,226 visits were scheduled and assigned to 1,155 daily rounds of care workers. Of the 9,226 scheduled visits, 8,976 were actually made; of the 1,155 scheduled daily rounds, 708 were carried out as scheduled and without changes. 333 rounds were rescheduled. In 34 cases, unplanned visits were added. In another 80 cases, both unplanned visits were added and the order of the visits to care-service users was changed.

Table 3: Number of care-service users included in the validation of the notification service during the test period

Care-service users visited	Care-service users visited with GPS	Care-service users visited with predictions
174	148	136

Source: CARU-FHWN-2021

In addition to the requests of the seven users of the voice assistant, the staff-scheduling data of visits for another 141 service-users (Table 3) were available for calculating the arrival time. Table 4 shows that GPS data was available for 5,093 scheduled visits. In 4,491 cases, a stay point could be matched, so the arrival time could be predicted in 88.18% of the cases. In addition, Table 4 shows that 198 scheduled visits (around 4%) were cancelled. Moreover, it can be seen that more visits lasted for a shorter time than was originally planned. A comparison of the actual start times of the visits with the predicted start times shows an average deviation of 33 min. Using the arrival time calculation, it is possible to forecast visits with an accuracy of 66 minutes (33 minutes earlier or 33 minutes later than scheduled).

Table 4: Comparison of scheduled and actual visit durations with stay-point matches used for prediction

Duration of visits	Scheduled visits*	Actual visits made*	Scheduled visits where a stay point match was used for prediction
< 5:00 min	1	50	1
5:00 – 9:59 min	44	341	43
10:00 – 14:59 min	184	597	157
15:00 – 29:59 min	2,028	1,569	1,635
30:00 – 59:59 min	1,686	1,373	1,569
60:00 – 119:59 min	740	633	696
> 120 min	410	332	390
Total	5,093	4,895	4,491

* visits during which GPS trackers were carried
Source: CARU-FHWN-2021

5 Discussion and Conclusion

Ambient/Active Assisted Living (AAL) projects aim to support older people and their care network in their everyday lives, and new technologies are key to achieving this. When older people receive home care, the information they and their relatives receive is often quite sparse, particularly when it comes to the accurate arrival time of their care workers. This often results in calls to the care organization, which places an additional burden on an industry already facing massive staff shortages.

With the development of a voice-supported ICT-based notification service, we took a step towards providing the predicted arrival time of care workers using voice only. The service was piloted during two three-month pilots in Austria and Switzerland.

The service we have presented here used two-stage data processing, of both low and medium accuracy, using staff-scheduling and movement data (GPS) to predict and notify the arrival time of the next visit of a care worker. The advantage of this approach is that information on the next arrival of a care worker was always delivered as soon as the staff-scheduling data was available. In addition, this approach makes it possible to consider only the stationary parts of a trajectory in the future.

The pilot was performed in two different settings (home care and assisted living). Usage data suggested that home-care service users (Austria) had a greater need to be informed about upcoming visits than people in assisted living (Switzerland), who were mostly aware of the fixed service hours of their concierges. 50% or more of the participants in Austria used the notification service every second day to receive information about the predicted arrival time of the care worker, which is perceived as a very frequent use of the service. As expected, the frequency of use declined over the pilot period.

The notification service relied on the functioning of the voice assistant and the Twilio (speech-to-text and text-to-speech service). Problems with these services resulted in lower use of the

notification service. In addition, failed attempts to trigger the service were not reflected in our usage data.

For the validation of the arrival time calculation/prediction, staff-scheduling and GPS data of 26 care workers visiting 174 care-service users in the test period were available. The results showed that it worked well when GPS data was available. Problems occurred when the order of the scheduled visits was changed, as the prediction was based on the original scheduled order. If the first service-user of the day was a new, unscheduled user and no rescheduling took place, the prediction for subsequent visits was inaccurate or impossible. Forgetting the GPS tracker in a car parked more than 250 m away from a visit also caused problems due to the parameters set. The same applied when home-care service users lived very close to each other. Forgetting the GPS tracker in a car and visiting multiple care-service users from a parking lot resulted in matching only one visit, as the system could not distinguish between the visits. Another challenge arose when care workers did not visit their care-service users and did not log the cancellation. In these cases, the system mistakenly assumed that the visit would take place. Many of the problems mentioned were organizational in nature and can only be solved by appropriate organizational workflows.

Future research may be interested in improving prediction ('high accuracy') by using traffic data. An additional approach to improve prediction accuracy could be to analyse care workers' visit patterns (e.g. if the order of two visits is always swapped by a care worker). If patterns emerge, artificial intelligence methods can be used to learn and incorporate them into the arrival time prediction. We also encourage future research to look into the potential of the stay point detection to improve care organizations' workflows. Currently, care workers must manually document the start and end times of a visit via a smartphone app. Using the stay point detection that is built into the notification service, visits could be automatically attributed to a stay point. To enable this, both the temporal and spatial accuracy of the matched stay points will be investigated in a future step.

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