

A Systematic Literature Review of Intent Sensing for Control of Medical Devices

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Abstract—The usefulness of medical devices, which require user input, is often limited by the control schemes that operate them. The recognition of user intent could enable far more intuitive control schemes that respond automatically to what the user wants the device to do. This paper provides a definition for intent, and then aims to systematically review current methods for sensing intent. It compares the accuracy of different methods and discusses how they might be combined. A systematic literature search was performed using IEEE Xplore, PubMed and Web of Science databases. 2311 papers were considered, reduced to 155 after review. All selected papers were assessed for quality using a checklist. The results identified and compared 15 sensing modalities used for intent sensing in a range of situations and applications that broadly fell into 12 distinct categories, with highly varying levels of accuracy. Several papers reached accuracy levels that could be suitable for everyday clinical application, but most work done on intent sensing to date has focused on activity transition classification, with fewer papers addressing task goal interference or predicting future actions. Further work can focus on the implementation of these kind of methods into a combined, context-aware intent-sensing control system.

Keywords— *Bionic prostheses, Intent sensing, Body sensing, Wearable technology, Sensor networks.*

I. INTRODUCTION

Interactions between humans and technology are fundamental to daily twenty-first century life. Better methods of interacting with devices can enable more intuitive control, increase productivity and improve the overall user experience. Human computer interaction (HCI) is a growing field of study, with possible implications in almost every workspace and living environment and many opportunities for improvement.

One particular area of great opportunity for research and development is that of intent sensing – the idea of using sensors to infer what the user actually wants to happen, without them having to actively indicate it. This could reduce or even eliminate the need for direct user input devices like buttons, hand-held controllers, etc. and has the potential to truly change the relationship between humans and technology.

This could be of particular interest for the medical technology industry. Clear examples of use cases consist of e.g. smart glucose control for diabetics, where research is underway to predict patients' activity in advance [1], and in prosthetics, where the majority of even the most sophisticated prosthetic upper limbs [2], are limited in their functionality by the necessity for users to manually select which grip they would like to use. Usually, selection may be done with an app [2], a button interface [3], or gesture control [4], but in all these

variations, it is indisputably clear this is nowhere near as intuitive as our natural control. It already has been suggested that humans are sensitive to small changes in the environment, which is reflected in our motor behaviour [5]. Previous work showed how object identification can potentially enhance grasping and create more natural interaction between user and environment [6]. With intent-sensing – understanding what the patient wants – these limitations could be overcome and a level of control comparable to that of a healthy human could theoretically be made possible.

The aim of this paper is to systematically review the literature regarding intent sensing in humans and to summarise the current state-of-the-art in terms of accuracy of these methods. This includes signals from not only wearable devices, but also portable devices such as smart phones and static sensors, which could be found in smart environments such as smart homes (a developing field with increasing potential in the healthcare industry [7]). The information generated by this technology could be used to assist in intent identification through the concept of context-awareness.

According to [8], intent sensing “includes recognizing the current activity, inferring the task goal, and predicting future actions.” In this paper, the statement is refined slightly in that it refers only to positive activity leading to some change in the user's state. This could include low-level action – e.g. reaching for an object, grabbing it – or a high-level action, e.g. cooking, cleaning, driving, etc. It does not refer to the passive observation of states, such as using gait analysis to classify the current mode of ambulation (e.g. walking or running) or using a pressure sensor in a bed to detect that the subject is lying down. It does, however, include transitions between states – for instance, starting running, beginning to climb stairs, getting out of bed, or slowing down. This paper therefore does not concern itself with simply monitoring and quantifying human activity/behaviour – but rather with the use of related sensors to infer when a human is transitioning, and if possible, predict what they are going to do next. Additionally, intent sensing is not considered to include additional manual intervention from the user. Only “natural” actions from the person are considered – if the user is required to indicate their intent in some way, e.g. by pressing a button or performing a specific gesture, this will not be considered true intent sensing.

Intent sensing is therefore defined as predicting future actions, passively recognising an activity state transition and inferring the subsequent task goal. Furthermore, to compare and contrast the performance and potential of each method of intent sensing, papers reviewed in this study must in some way quantify the accuracy of their system.

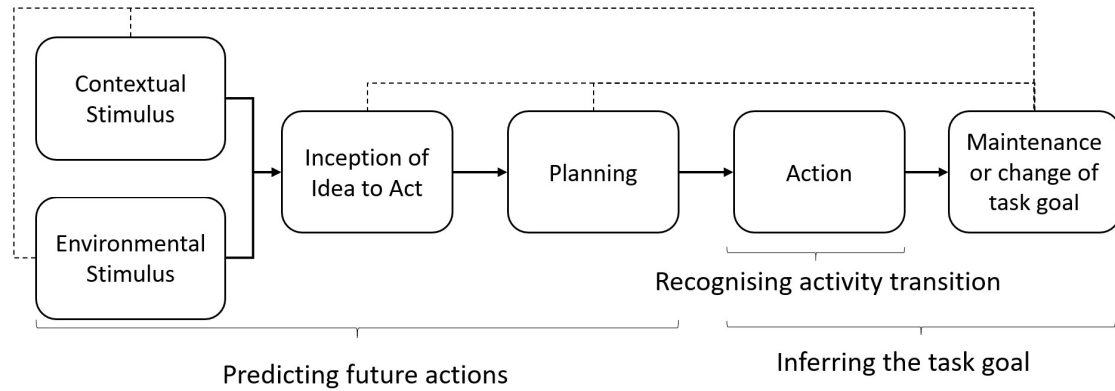


Figure 1 – Flowchart detailing the proposed theoretical flow of task performance. The figure highlights the three aspects of intent sensing defined in the scope of this paper. Contextual stimulus refers to factors such as the user’s routine, emotional state, previous experience, desires and instincts which may lead to action. Environmental stimulus encompasses external factors such as proximity to stairs, indicating a user might want to climb them. The maintenance or change of task goal involves continuous re-assessment of the previous steps which may or may not lead to a change in the current action. Feedback loops between the stages (dotted lines) are not considered for the intent definition at this stage.

This literature review will therefore summarise the existing methods of human intent sensing, compare their accuracy, and subsequently assess their potential for the design of an intent-sensing operating system.

The components for a new definition of intent (see Figure 1) are further described below to provide additional clarity beyond the originally proposed definition.

A. Predicting Future Actions

The first key aspect of intent sensing identified in the definition is prediction – determining what a user is about to do before it happens. Less work has been done on this than activity transition recognition, and performance results on this aspect are highly mixed. The prediction of future actions is essential, as it allows the system to make the necessary changes on time. The transition and goal detection can be determined as it happens, but the prediction needs to be completed beforehand. This is the main difference of this component compared to the following two.

Some studies have integrated prediction into a smart-home activity transition recognition system by tracking user movement and building a profile of the user’s typical routines. This allows some degree of high-level prediction, e.g. “the user normally goes to the bathroom before bed.” [9]

On a lower level, wearable sensors have been used to predict upper-limb reaching actions through the use of electroencephalography (EEG), but only over time periods of up to a second. [10] Locomotion events can also be predicted through wearable sensors, but again, the timeframe for this prediction is rather short. [11]

Increasing the time span would allow for the system to be more prepared regarding the intent of the user, but this is likely to result in an increased uncertainty in terms of accuracy.

B. Recognizing the Activity Transition

Another important part of intent sensing is the concept of activity transition recognition – identifying actions that a user is currently doing or has recently done, specifically when they are changing from one activity state to another. Much of the work in this field has focused exclusively on activity transition recognition for a whole range of applications. [12]

Some activity transition recognition techniques leverage the concept of a “smart home,” using networks of sensors

placed strategically around the user’s home to detect changes in their current activity of daily living. [13] Often this is done by tracking the user’s location, as they move from bedroom to kitchen to living room – however, this gives only a high-level classification of the activity transition without observing specific movements. [14]

Individualised sensors – e.g. pressure sensors in the bed, smart detection of kettle turning on, etc. allow more precise classification of activities, but are obviously fundamentally limited, in that each sensor is specifically designed for sensing one particular task. [15]

Portable devices have also had their data leveraged to perform activity transition recognition. Smart phones and watches contain sensors such as accelerometers and microphones which can be used to passively gather data to classify user activities throughout the day. These are primarily used to identify periods of exercise, but it is feasible that data from mobile devices could contribute towards an activity transition recognition sensor network. [16]

In intent sensing, any activity recognition should feed into the recognition of an activity transition. The user will always be in a certain state when sensing is starting and the system is preparing itself to deal with the next state when a transition is detected. This is a fundamental step of intent detection.

C. Inferring the Subsequent Task Goal

The final component of intent recognition as defined above is inference of the task goal, which includes identification of the motor goal – the neurally planned outcome of a current physical activity, which may be (automatically) corrected in the event of a perturbation [17]. However, the concept of task goal as considered in this definition extends beyond the motor goal, towards the higher-level goal of a current activity transition, e.g. reaching out in order to pick up a cup, approaching the stairs in order to climb them, or even moving the hands in order to turn a steering wheel and therefore park a car. In a sense, it is a short-term prediction at the end of the current activity. This is distinctly different from predicting future actions. Inferring the task goal refers exclusively to identifying the objective of a task which is currently underway, whereas prediction of future actions relates to anticipating tasks which have not yet begun.

Several studies have taken place into the inference of task

goals using eye tracking, to identify objectives in activities of daily living [18] or to predict the toy a child would like to play with. [19] Work has also been done to understand the goals of drivers when manoeuvring on the road, with warnings to indicate if the inferred manoeuvre could be unsafe. [20] This part of the definition is concerned with identifying what the goal of the activity will be once the transition phase has been entered. The transition phase allows the system to be aware of a change, whilst the activity goal will indicate what the system needs to do directly after transition.

D. Example

To more clearly explain the three aspects of intent sensing identified in this definition, an example is provided. A camera can be used to detect a glass of water on a table, which can represent an environmental stimulus for a person. The person can reach for the glass because they would like to drink from it. However, the time of day and length of time since their last drink (contextual stimuli) can be used as well to predict that they may reach for the glass. This can even happen before the idea has even occurred to the person. While the confidence of this prediction may initially be low, it is likely to increase over time as the action becomes more imminent. Cues taken from a person's body language and perhaps even brain activity can indicate the person is starting to act on their planning. All these aspects can be considered for intent sensing.

Then, when the person begins to reach, the activity transition from a rest state to a reaching motion may be recognised, for example by an electromyography (EMG) monitoring system on the arm.

The task goal of the arm movement is to reach the glass, which may be inferred through eye-tracking, or by estimating the trajectory of the reach. One might even be able to detect a goal change – for instance, the glass is pushed away instead of picked-up.

E. Limitations

The proposed definition of intent works well in the context of controlling medical devices, but could be further optimized for broader use beyond the scope of the current paper. The literature offers conflicting use of the word “intent”, and ambiguities may arise in certain applications as to whether or not they should be considered “true” intent sensing. Examples of this include wheelchair navigation through doorways [21] or the prediction of web links that a computer user may intend to click on [22], which by this paper's definition would be considered intent sensing, but it might not be currently referenced as such.

F. Objective

This review paper will focus on studies related to intent (as previously described in this section) in some way. As such, it should be noted that the review will not include wider contextual tools which may have potential applications for intent detection, such as the recognition of obstacles or the learning of daily routines. Literature will only be included if attempts were made within those studies to apply measurements and observations directly related to intent sensing. In addition, this review accepts articles that utilise sensor information in their predictions of intent. Purely theoretical papers, or papers which exclusively use self-reported intent, will not be included.

The overall objective of the review will be to assemble all existing literature on intent sensing as previously defined, assess its quality and categorise it according to which sensors it uses. The literature will also be clustered according to the components of the intent sensing definition it addresses, and the general distribution of types of intent measured will be determined. The results identified will then be used to assess each sensor type's suitability for intent sensing and highlight areas in the literature where more research is needed. Mann-Kendall tests (a well-established statistical test for trend analysis [23]) will also be employed to quantify trends over time in numbers of papers related to each sensor type and intent sensing aspect to indicate areas of particular growth.

II. METHODS

A. Search Strategy

This paper will perform a systematic review of existing methods of intent sensing, following the guidelines and principles of Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) [24]. The search strategy consisted of the keywords: (Accuracy OR Sensitivity OR Specificity) AND (((Predict OR Prediction) AND (Activity OR Behaviour)) OR Intent) AND (Sensors OR Sensor network OR BSN OR Wearable Sensors). This was used to search three databases: IEEE Xplore, Pubmed and Web of Science, returning results that included these search terms in their keywords, title or abstract. The search covered all published papers up to and including January 2020.

B. Study Selection

All results were first screened by reviewing the abstract and eliminating those which did not satisfy conditions for relevance according to the definition of intent sensing discussed in Section I. As this definition is quite nuanced, a simple selection of keywords alone was not sufficient to fully determine each paper's relevance. A second reader also reviewed the results, and in instances where the readers' opinions on relevance conflicted, a discussion took place until both readers were in agreement. If no agreement could be reached a third reviewer was required to adjudicate.

The inclusion criteria were:

1. Must be written in English.
2. Must be peer reviewed.
3. Must refer (either implicitly or explicitly) to at least one of the three aspects of intent sensing identified in this paper's definition – predicting future actions, activity transition recognition, and goal inference.
4. Must not refer only to activity recognition without identification of transitions between states. However, the inclusion of activity recognition alongside valid components of intent sensing is acceptable.
5. Must contain some measure of accuracy or reliability, i.e. not simply a description of a theoretical method.

Each study had the following data recorded: Title, First Author, Year, Number of Participants, Participant Details, Aim, Outcomes, Sensors Used and Intent Aspects Identified.

C. Quality Assessment

The quality of the papers was then reviewed using an eight-item checklist. The criteria used were based on those in [25], which were themselves based on the Joanna Briggs Institute critical appraisal checklist for cross-sectional research [26], “adapted to be applicable for Machine Learning applications”. The final modified checklist is shown in Table 1. For some papers, not all eight criteria were relevant, so they were discounted whenever they were not applicable. For each article, the number of relevant checklist criteria satisfied was counted, and divided by the total number of relevant criteria to give a percentage score. This percentage score was considered to represent the paper’s quality, and the papers were then ranked in order of these scores.

The quality assessment was then confirmed by a second reader, and again, any disagreements were discussed until both readers agreed or a third adjudicator was used.

D. Categorisation

The papers were then categorised according to the sensors used, the intent components identified and the type of action intent measured, with the numbers of articles falling into each category counted. The accuracies reported by papers in each of the categories were recorded. It should, however, be noted that the accuracy metrics used varied from paper to paper and are not always directly comparable.

For example, [27] used EMG and kinematic sensors to classify between seven different activity transitions with 95% accuracy, whereas [28] used electroencephalography to distinguish between a reach motion and rest with 72% accuracy. These two studies differ in complexity, and so the accuracy comparison should be used as a general guide only.

E. Trend Analysis

The numbers of papers published each year involving i) each aspect of intent sensing and ii) each sensor type were recorded, and the general trend analysed using a Mann-Kendall test, assessing paper count per year between 2005 and 2019. The resulting values were tabulated for comparison.

III. RESULTS

A total of 2808 papers were screened across the three databases, with 497 duplicates identified and removed. This left 2311 papers for abstract-reviewing, which subsequently reduced the number to 155. None of the papers were excluded based on their main body contents, indicating the keywords chosen were effective. Figure 2 shows a flowchart of the reviewing process. Qualitative synthesis was then performed on these remaining papers (see supplementary material).

A. Quality Assessment

The quality ratings of the papers varied, with a median of 81%, and an interquartile range of 63%-100%. 44 papers had a perfect 100% score, and no papers scored 0% - the lowest quality score recorded was 31%. All papers reviewed had at least some description of aim/objective, though this varied in clarity, satisfying or partially satisfying item 1. Items 2 and 5 were not applicable to papers which did not gather data (as they used a pre-existing dataset), so these were only evaluated for 104 of the papers. The percentages of papers satisfying each part of the intent definition are shown in Table 1.

B. Categorisation

Dividing the papers into categories based on the earlier definition revealed that 88% discussed the activity transition recognition aspect of intent, 6% discussed goal inference, and 17% discussed prediction of future actions. There was little difference in quality across the three categories, with the median quality remaining at ~75% for all three.

Dividing the papers reviewed by the sensing method revealed that 15 different sensing methods were used to detect intent. These were: computer vision, Electroencephalography (EEG), Electromyography (EMG), Mechanomyography (MMG), Force Myography (FMG), angular rotation measurement, motion tracking, gaze tracking, accelerometers, smart phone sensors, smart watch sensors, smart home sensors, force/pressure measurements, self-reporting and Electrocardiography (ECG). The distribution of these is displayed in Figure 3, and a comparison of the accuracies in the studies for each sensor type is shown in Figure 4, with full details given in the supplementary material.

Item	Description	Valid for (# of papers)	Satisfied by (% of papers)
1	A clear objective and description of inclusion criteria of the study population (i.e. selection of subject group, or time series data) or statement of aim prior data to collection?	155	90%
2	A detailed description of the study population (i.e. how are the subjects recruited?)	103	51%
3	A clear description of the data source and how data was collected (i.e. clearly describe method of measurement.)	155	97%
4	A valid and reproducible data collection and measurement method (i.e. Was the data measured in a reliable way?)	155	63%
5	Attainment of ethical approval. Was the ethical issue (subject confidentiality) considered?	100	37%
6	Were findings and implications discussed in detail?	155	74%
7	Were the outcomes measured in a valid and reliable way?	155	97%
8	Was appropriate cross-validation and evaluation method used?	155	90%

Table 1 – Quality assessment checklist. The number (#) of papers for which a certain item was valid is given, as well as the percentage of valid papers that satisfied the criteria.

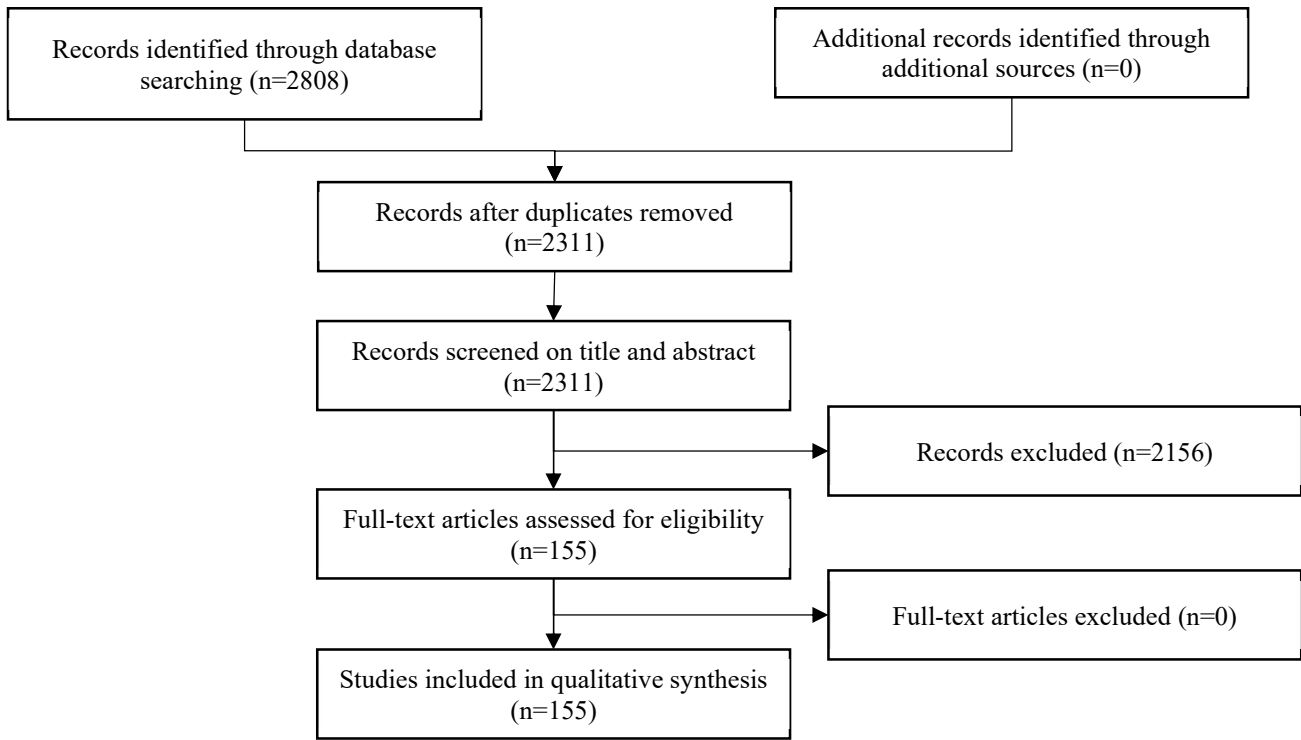


Figure 2 - Flowchart of the inclusion/exclusion decision making process used to determine which papers should be used in the study.

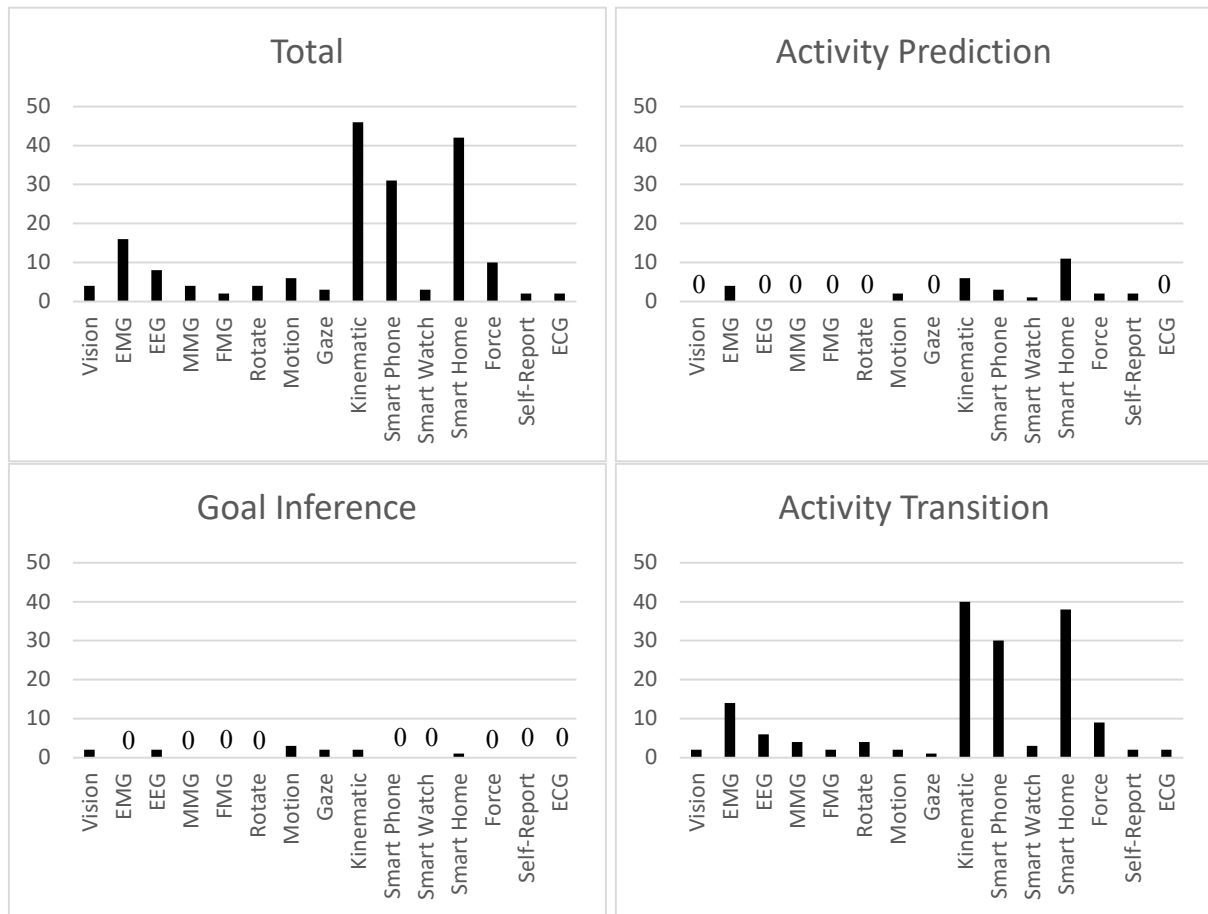


Figure 3 – Breakdown of number of total papers (vertical axis) according to sensor type (horizontal axis), as well as the number satisfying each component of the intent definition. Multiple sensors can be used in the same paper. Vision relates to computer vision; Electromyography (EMG); Electroencephalography (EEG); Mechanomyography (MMG); Force Myography (FMG); angular rotation measurement (Rotate); motion tracking (Motion); gaze tracking (Gaze); kinematic sensors (Kinematic); Smart phone sensors (Phone); smart watch sensors (Watch); smart home sensors (Home); force/pressure measurements (Force); Electrocardiography (ECG) and self-reporting (Self). 0s are used to highlight sensors which were not used in any papers for a particular intent-sensing aspect.

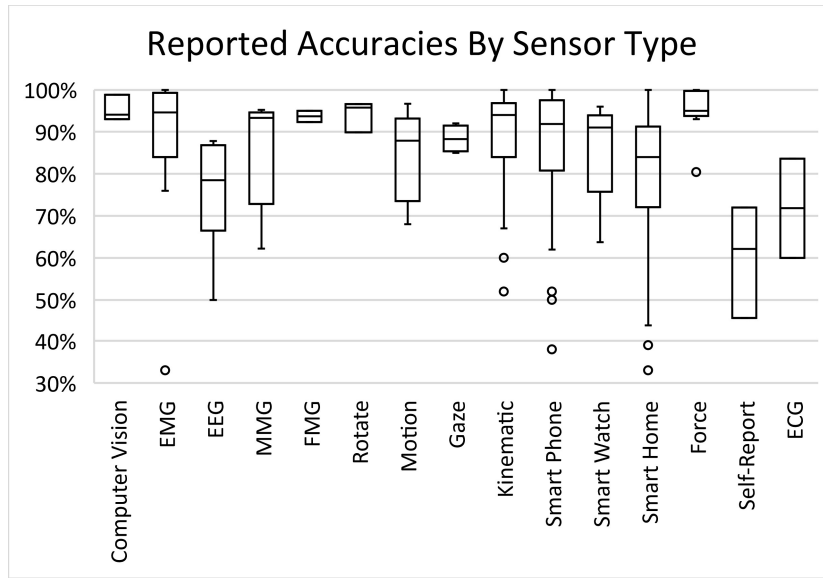


Figure 4 – A box-and-whisker plot to show the range of accuracies reported in the results across the 155 papers analysed, with accuracy (%) on the vertical axis and sensor type on the horizontal. The boxes show the upper and lower quartiles, the middle line shows the median, the whiskers show the range, and the points indicate outliers. A point is considered an outlier if it is larger than 1.5 times the IQR of the third quartile or 1.5 times smaller than the IQR of the first quartile. Care should be taken when interpreting this figure, as conditions and methods vary between papers and are not “like-for-like”.

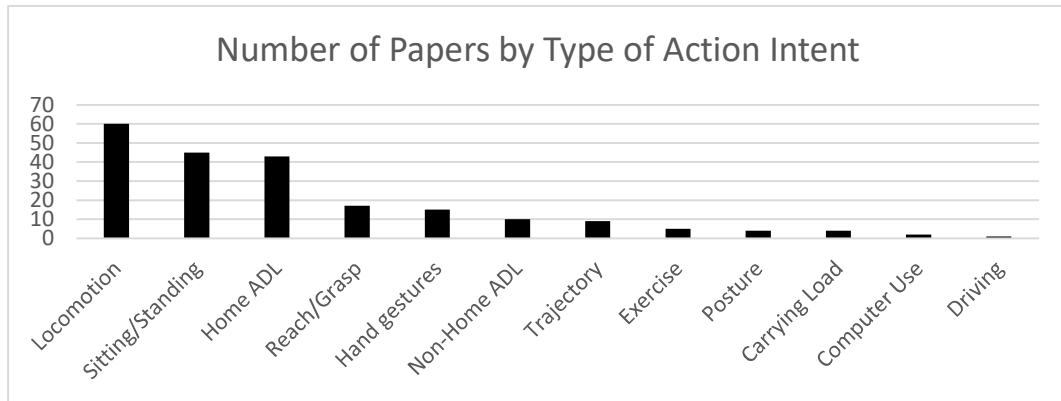


Figure 5 – A plot displaying the distribution of papers, grouped into categories by type of action intent studied. The number of papers is displayed on the vertical axis. Note that some papers included multiple types of action intent, so the sum of the columns is greater than the total number of papers.

In total 24 (15%) of the papers reviewed used more than one type of sensor, and only one paper used more than two (three sensor types were used). It should be noted that this occurrence of multiple sensors in some papers will mean the values displayed in Figure 3 add up to greater than the total number of papers.

Dividing the papers into categories to show the type of action intent used revealed twelve broad groups: locomotion, sitting/standing, general activities of daily living (ADLs) at home and outside the home, reach/grasp tasks, hand gestures, estimating the user’s trajectory, predicting posture intent, load-carrying tasks, and tasks related to exercise, driving and computer use. The distribution of these is shown in Figure 5.

Across the three aspects of intent sensing discussed, the accuracies reported by those papers concerned with activity transition recognition ranged from 33-100%, for goal inference, 73-98.8%, and for prediction, 40-100%. Information on the accuracy of each included paper can be found in the supplementary materials.

C. Trend Analysis

The cumulative number of papers published per year involving each intent sensing aspect is shown in Figure 6. The results from the Mann-Kendall tests performed on the number of papers published per year according to the intent sensing aspect and sensor type categories are shown in Table 2.

IV. DISCUSSION

A. Screening

The results of the literature review revealed much about the current state of the field of intent sensing. Many of the papers discarded during screening refer to intent, but do not align with the definition given in this paper. Instead, they refer to the use of a control interface – e.g. the use of particular pre-programmed gestures – in order to operate a device.

This paper does not consider this to be true intent sensing, as to achieve this, the system should sense what the user is trying to do from their natural actions, and not require them to perform a particular (additional) action in order to inform the

sensing system of their intentions.

B. Aspects of Intent Sensing

Referring back to the three aspects of intent sensing discussed in the introduction: activity transition classification, goal inference and activity prediction, the existing literature varied in number of publications across the three fields. It should be noted that while a higher minimum accuracy was reported for prediction and goal inference than was reported for activity transition recognition, this is more likely to be simply due to the papers having different assessment criteria. It is also intuitively easier to make more accurate observations about current events than to predict future events.

No studies showed evidence of combining the prediction and goal inference aspects, and by extension none attempted to combine all three aspects of the intent detection definition into one unified system, so a system which does integrate all three would be a strong contribution to the literature.

C. Activity Transition Classification

The vast majority of the work that has been done to date is on activity transition classification, identifying changes in what the person is currently doing at a particular time. 88% of the papers reviewed focused on this aspect of intent sensing. While identifying a subject's current transition between activities is an important stage of intent identification, it only captures information up to the present moment, and does not consider what the user will do next or why they are doing it, so this process must be combined with other methods to more completely identify user intent. The recognition of gait transitions seems a particularly well-developed field with many high-accuracy methods available, and multiple studies report accuracies in the region of >99% [29][30].

D. Prediction

The prediction aspect of intent sensing is the second-most explored of the three, with 17% of papers referring to this.

Category	N (no. papers)	z-value	p-value
Total	155	4.33557	0.00001**
Intent Aspect			
Prediction	27	3.72137	0.00020**
Goal	10	2.20593	0.02739*
Transition	137	4.08640	0.00004**
Sensor Type			
Environment Vision	4	2.36520	0.01802*
EMG	16	2.95832	0.00309**
EEG	7	1.59631	0.11042
MMG	4	1.43346	0.15173
FMG	2	0.78840	0.43046
Rotate	4	0.96357	0.33526
Motion	6	2.58378	0.00977**
Gaze	3	0.42894	0.66797
Kinematic	45	4.02611	0.00006**
Smart Phone	30	3.62825	0.00029**
Smart Watch	3	2.03810	0.04154*
Smart Home	42	2.98249	0.00286**
Force	10	1.74850	0.08038
Self-Report	2	0.78840	0.43046
ECG	2	1.50513	0.13229

Table 2 – Results from Mann-Kendall tests performed on the number papers reviewed by each year of publication, categorised by intent aspect and sensor type, to indicate trends in interest over time. Note that some papers included multiple sensor types, so N total is less than the sum of the sensor types. * indicates p-values <0.05. ** p-values <0.01.

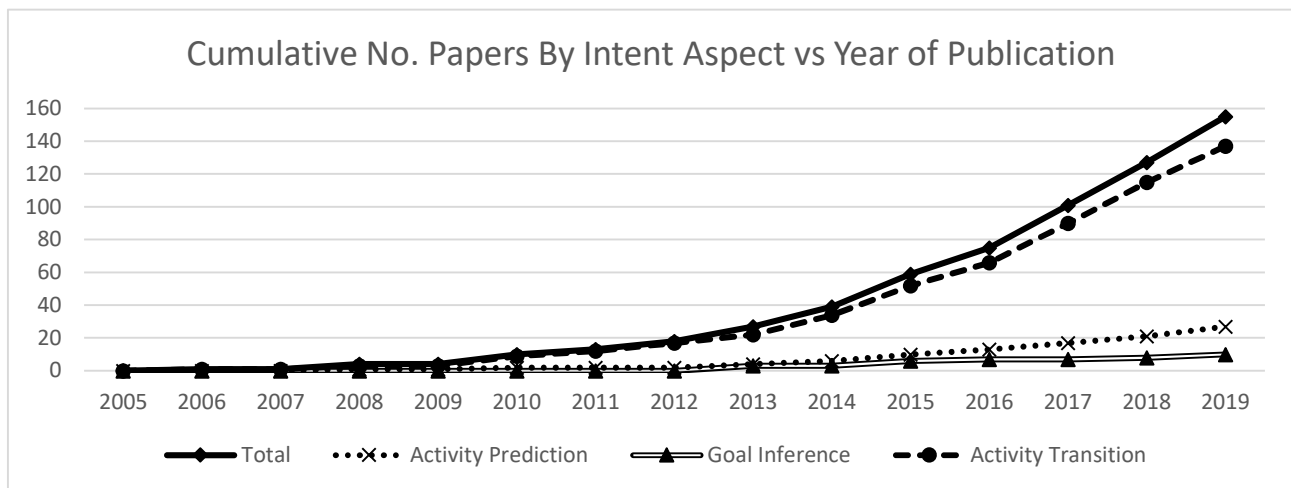


Figure 6 – A line graph displaying the cumulative number of papers utilizing each aspect of intent sensing vs the year of publication. The vertical axis shows the cumulative number of papers and years are displayed on the vertical axis.

Results were mixed in this area, and the size of the time window selected seemed to have a strong impact on the performance of the system – predictions that are only a second in advance of a particular event understandably tended to have a higher accuracy than those predictions performed five seconds in advance. This was demonstrated in particular by [31], with prediction accuracy dropping from >80% to >60% when the time window was doubled. Alongside these studies, a number of new models, including Hidden Markov machine learning [32] and graph-based [33] models to learn typical patterns of user behaviour, have been developed for use in predictive classification, which have shown promising results.

E. Goal Inference

The goal-inference aspect of intent-sensing was explored very little, with only 6% of papers referring to it, indicating there is room for more research and exploration. In a similar way to the prediction component, it should be noted that accuracy of the goal inference increases as the action being studied progresses in time – in general, it is harder to predict an action's goal moments after its beginning than it is when it is nearly complete. This is demonstrated in [34], a study inferring the goal of a driving manoeuvre to evaluate it for safety, where accuracy of the inference increases from 80% at 0.5 seconds after activity inception to 90% at 1 second after. It is also shown that a lower classification accuracy is found when more possible goals are available. [35] [36] Notably, while some studies have attempted goal inference in non-medical settings, no system has yet been developed to incorporate task goal inference into an intent recognition system for a medical device, indicating there is significant scope for development in this field.

F. Comparison Over Time

Figure 6 shows the cumulative number of papers related to each aspect of intent sensing plotted against the year of publication. Since the first intent sensing paper published in 2005, papers in the activity transition category have been by far the most numerous, followed by activity prediction and goal inference. This order has been maintained, with the gap widening over time. The total number of new intent-sensing papers every year has generally increased, with the cumulative graph getting steeper and the Mann-Kendall test showing a positive trend, indicating a growth in interest in the field of intent-sensing in more recent years. Trend analysis suggests the fields of all three aspects of intent are growing year on year, but goal inference is growing more slowly. As this is an essential component of a complete intent-sensing system, accelerating research in this relatively undeveloped field would be of benefit to the development of intent sensing as a whole – more so than activity transition classification, which already appears to be developing rapidly.

G. Sensing Methods

1) Computer Vision

Computer vision is the automated interpretation of data from visual sensors, e.g. cameras. Here, it is used to refer to the observation of the environment around the user – the use of visual sensors to track the motion of the user has been categorised as Optical Motion Tracking. Environmental computer vision has been utilised in the areas of classification and goal inference [37]. Work on it has been relatively sparse, with only four papers reviewed incorporating it. It has been shown to have potential in goal inference, identifying whether a user's goal was to climb stairs with a ~99% accuracy [38]

and planned interaction with objects yielding a ~93% accuracy [36], but further studies are needed to apply it to more general classification of activities of daily living, rather than to individual, specific situations. Depth sensing was also able to perform activity transition classification between locomotion modes such as walking, running and stair ascent with an accuracy of ~94% (quality score 75%) [39], but computer vision is rarely used for this purpose.

2) Electromyography (EMG)

Electromyography is the process of recording and evaluating the electrical signals produced by muscles during activity, driven by the motor neurons [40]. EMG's use for intent is growing rapidly according to trend analysis, and is used in sixteen papers in total, dividing into twelve papers to detect activity transitions, and two papers with some predictive element (and two papers using both). However, no papers have used it for goal inference. Results for activity transition classification in the papers reviewed showed consistently high-accuracy (>90%), and while results in the four papers considering prediction were mixed, of particular note was the use in a high quality paper (score 88%) of EMG to predict sit-to-stand transitions ~130ms before the subject leaves their seat with an accuracy of ~99.5% [41], supporting EMG's potential in predictive control.

3) Electroencephalography (EEG)

Electroencephalography is the monitoring of electrical signals from the scalp, which are analysed to extract information about the underlying brainwave signals [35]. EEG was used in seven papers, primarily to perform activity transition classification, where both results and quality of papers were mixed. It was not used in prediction, but in two papers goal inference was attempted, with accuracy varying between 40% and 80% in one – a brain computer interface [35]. In the second goal-focused paper, the anticipated force of an in-progress grasp was predicted, but the best median correlation coefficient between prediction and reality was only 0.51 [42]. Across the seven papers, the highest accuracy reported was ~86% [43] – high, but not high enough for reliable control of a medical device. In general, the papers show positive results, suggesting EEG has already gained traction as a possible intent-sensing method. Nonetheless, the variance and limitations in the reported accuracy in the papers reviewed do not support this as a practical intent sensing method for medical devices at the moment.

4) Mechanomyography (MMG)

Mechanomyography is the measure of physical vibrations within the muscles during activity [44]. MMG was used in four papers to recognise activity transitions, with accuracy results ranging between ~60 and ~95%. No papers used it for prediction or goal inference. This low number of papers and exclusive focus on only one aspect suggests limitations in the existing work that has been done with MMG for intent sensing and that other sensing types may be more readily applicable to identify intent, based on the current available evidence.

5) Force Myography (FMG)

Force myography is the use of force sensors to capture the expansion and contraction of a surface muscle [45]. FMG was used in only two papers, again to recognise activity transitions, but not to predict or to infer goals. One was able to determine postures during drinking with an accuracy of 92% [46], and the other classified positions of a robotic glove with an accuracy of 95% [47]. These are promising results for activity

transition classification, but again the low number of papers and exclusive focus on activity transition suggests more studies are needed to determine the extent of FMG's applicability to a full intent sensing system.

6) *Angular Rotation*

The angular rotation of joints was used as a sensing input for four of the papers, all aiming to perform recognition of transitions between activities. Results were positive, with one good quality paper (score 75%) classifying motion patterns with an average accuracy of ~96% [48], but again the work was limited entirely to activity transition and no evidence is presented in the papers to suggest potential application in goal inference or prediction.

7) *Optical Motion Tracking*

Optical motion tracking – the use of visual sensors to detect and analyse human movement, often through the tracking of markers [49] – featured in six papers, covering all three aspects of intent sensing and achieving >93% accuracy in all areas. This successful, high accuracy coverage of all aspects of intent indicates motion tracking has strong potential for intent sensing, and more research should be undertaken on this topic - especially, exploring its utility in more complex and realistic environments, as the required cameras are unlikely to be available outside of controlled spaces.

8) *Gaze*

Gaze tracking monitors the user's eye movement to determine their region of focus and intention [35]. Human gaze analysis was employed in three papers, once to identify activity transition and twice to infer the goal of the current activity. Trend analysis does not support significant growth in the field. It was used successfully in identifying current computer tasks to successfully speed up preparation of materials, but accuracy results for this are unclear and the quality score is low at 43% [22]. The remaining two papers performed goal inference with accuracy >80%, high but not at an acceptable level for reliable control. This suggests there is evidence for gaze as a possible input for goal inference, but no strong evidence for use in prediction or activity transition.

9) *Kinematic Sensors*

Kinematic sensors detect and measure motion, and include accelerometers and Inertial Measurement Units (IMUs). This was the most common type of sensing input and is growing the most rapidly according to trend analysis, appearing in 45 papers across all three aspects of intent sensing, with 37 papers using them for activity transition classification, two for goal inference and three for prediction. A total of three papers used them for both activity transition classification and prediction. Naturally, across so many papers, accuracy results covered a wide range depending on the scenario investigated. Nonetheless, many reported a performance of >90%. The versatility of kinematic sensors (across all three aspects) and the breadth of the already existing research on them makes them a strong candidate for use in an intent-sensing system.

10) *Smart Phone*

Modern smart phones include a variety of sensors, including accelerometers, location tracking and microphones, and are the second-most rapidly growing field for intent according to trend analysis. Smart phones were employed in 30 studies, with 27 of them focusing solely on activity transition classification and three incorporating both activity transition classification and prediction. Results varied, with some papers reporting accuracies >95% and some as low as

60% or even ~40% depending on the situation. While this suggests that they may be useful for activity transition sensing with only a small amount of evidence towards application in prediction, the ubiquity of the smart phone means it is highly likely to be available to users at any given time. Therefore it may provide additional (if limited) sensing information to an intent sensing system at little-to-no additional cost.

11) *Smart Watch*

Much like smart phones, smart watches include a variety of sensors, but are only worn on the wrist. They were used in only three of the papers reviewed, with two of these for activity transition classification and one with both classification and prediction (though the accuracy results for the prediction are unclear). The placement on the wrist provides superior identification of arm movements, with a paper classifying physical activity transitions with accuracy ~96% [50]. However, more research is needed before clear statements can be made about the potential of smart watches in general for intent sensing.

12) *Smart Home*

Smart homes are a developing technology involving the placement of sensors around the user's living space, with applications in activity transition recognition, energy monitoring and healthcare [51]. Trend analysis suggests smart homes are a rapidly growing field for intent, and a total of 42 papers used smart homes/environments across all three aspects of intent sensing (though only one paper focused on goal inference). Once again, the large number of papers resulted in a wider range of accuracies for activity transition classification, but many of these were in the >90% accuracy range. For prediction, accuracies ranged between 60% and 90%, and for the goal inference paper, the aim was identified by mining location trajectories as the user moved around the environment, with accuracy between 84% and 96% [52] (though the quality score for this paper was only 43%). The breadth of research regarding smart homes and their ability to cover all three aspects of intent sensing makes them good candidates for use in a unified intent system.

13) *Force/Pressure*

Ten papers used strategically placed force and/or pressure sensors, some positioned in shoes and some included in tactile arm braces. All of these focused on activity transition recognition, though two also incorporated prediction – although the accuracy of the prediction component in these cases is unclear. Accuracy of classification using these sensors is consistently high, achieving >90% in all but one of the papers, which achieved only 80% (quality score 71%) [53]. The use of force sensors shows high potential in activity transition classification – particularly if they can be built into a wearable device – but there is not clear evidence in support of them for the other intent sensing aspects.

14) *Self-Reporting*

Self-reporting of activities, in which the user manually records what activities they perform throughout the day, was used in two studies to build up a data set of the user's daily routine and provide context for current activity identification, as well as predictions of the future. While results were highly accurate (>95%), self-reporting of activity is not a viable option for automatically identifying user intent without the need for manual intervention. Self-reporting was only included for articles that already reported on a sensing

technology, thus only a limited set of the self-reporting literature is contained in these results.

15) *Electrocardiogram (ECG)*

Electrocardiography is used to monitor the rhythm, rate and electrical activity of the heart [54]. In two studies, ECG was used to help identify physical activity, determining whether a person is currently exercising or not, which is not considered by this paper to be intent sensing. While this alone would not satisfy conditions for inclusion in this review, in both studies, ECGs were also used in combination with accelerometers which were being applied in an intent sensing context. As a result, however, there is little information on the intent-sensing performance of ECG sensors by themselves. However, the anticipatory response in heart-rate shortly prior to physical activity is a well-documented phenomenon [55] and this could be promising sensor modality to research further in future dedicated intent sensing studies.

H. *Multi-Modal Sensing*

Many studies used a single sensing method to identify user intent under controlled conditions - however, combinations of two or more independent sensing methods should be able provide higher accuracy [56]. Relatively few studies attempted to do this, with only 15% of studies using more than one sensing method and only one with three methods, again indicating there is room in the research for exploring multi-modal intent sensing, and a multi-modal network featuring several of these methods would be unique in the literature.

I. *Comparison*

The reported accuracies of the fifteen sensing methods were compared in Figure 4. Care should be taken interpreting this figure, as the methods varied greatly from paper to paper and accuracy metrics used are not “like-for-like”. However, the graph does indicate the general trend of the results in the literature. Excluding outliers, the greatest range was observed in papers using smart home sensors, but this was also one of the most widely-used sensing methods, occurring in forty two papers. The smallest range was found for FMG, but as this was only used in two papers, this is not necessarily unexpected.

By comparing median, upper and lower quartiles, papers utilising self-reporting and ECG showed the lowest accuracies, whereas computer vision, EMG, rotation and force sensing showed the highest.

Table 2 also indicates the trend in no. papers published using each sensing modality. It suggests the most rapidly growing sensing fields for intent are EMG, optical motion tracking, kinematic, smart home and smart phone sensing.

J. *Types of Action Intent*

The types of action intent measured in the papers reviewed fell broadly into twelve categories, shown in Figure 5. By far the most common intent measured was locomotion – transitions between walking, running, ascent and descent. Sit/stand transitions were often included with locomotion, but also separately in many cases. The next most popular category was Activities of Daily Living (ADLs) at home, which refers to the classification of a wide range of complex task transitions, such as cooking, cleaning, watching television, etc. This featured commonly in smart home systems. Upper-limb intent sensing was less common but often used with reach/grasp tasks and gesture recognition. Other categories were rarer, including ADLs outside the home (e.g. commuting, or at work), prediction of subject movement

trajectories, posture intent, and specific activities related to exercise, carrying loads, using computers and driving.

These distinct categories demonstrate the breadth of actions that contribute towards intent. The relative focus on the top three most popular categories suggests there is scope for more research into more general intent sensing systems covering a wider range of possible actions in detail.

V. CONCLUSION

In conclusion, it has been shown that much preliminary work has been done on certain components of intent sensing, such as the classification of transitions between activity states. However, comparisons between research outcomes remain difficult due to a lack of a well-established definition. A common framework for the definition of intent sensing can further support this growing field. The definition provided in the current paper can be built upon by other researchers.

Fifteen different sensing methods were used in the papers identified, for a range of contexts and applications that broadly fell into twelve categories. Of these sensing methods, only motion tracking, accelerometers and smart-home sensors were shown to be studied across all three aspects of intent sensing. Currently, these fields show the greatest potential for intent-sensing covering the full definition of intent. The accuracies reported were mixed and depended on the research aim of each paper reviewed, so care had to be taken to avoid drawing misleading conclusions by contrasting incomparable accuracy assessments. More standardisation in testing (perhaps involving pre-determined sets of actions) would allow for more insightful comparisons. Nonetheless, many of the papers reported high levels of accuracy, which gives confidence in intent sensing as a promising, practically applicable field, and observations were made that prediction accuracy increased firstly as the length of anticipatory time decreased, and secondly as the number of possible options decreased.

This review has focused on a very specific scope, covering only papers with direct relevance to intent sensing as previously defined. Further literature review studies addressing related fields and with wider, more general scope can be useful to place intent sensing within the broader concept of human behaviour.

To further the field of intent sensing, it is suggested that future work could attempt to combine data from multiple sensing systems or scenarios to further increase the ecological validity of these systems. Particular attention should be paid to the goal-inference and prediction aspects of intent sensing, as these have been explored relatively little despite forming an important part of the concept of intent sensing.

This would allow a medical device to really work together with the patient across a range of activities and offer a new way of bringing value to the user. True device symbiosis creates unique challenges for the research community, but it will also offer a more holistic development pathway for medical devices. It could enhance device responsiveness and ease of use, whilst enabling more precise, advanced control without the need for additional control interventions. These improvements could reduce device abandonment and increase quality of life for users, with a potential for positive long-term impact across the (medical) device industry and beyond.

The proposed definition introduced in this paper is the first endeavour to provide a more robust framework for the development of intent sensing technology. The definition does

not aim to be suitable outside of the biomedical engineering field, but it could be further specified to increase the utility in other domains. Nonetheless, this proposed definition will hopefully spur further discussion in terms of creating a robust framework for intent sensing assessment, which could accelerate progress towards true intent sensing becoming ubiquitous in the not-too-distant future.

VI. REFERENCES

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