

# Clustering Approaches for Gait Analysis within Neurological Disorders: A Narrative Review

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## Keywords

Gait analysis · Instrumented gait analysis · Clustering · Neurological disorders · Clinical decision support systems

## Abstract

**Background:** The prevalence of neurological disorders is increasing, underscoring the importance of objective gait analysis to help clinicians identify specific deficits. Nevertheless, existing technological solutions for gait analysis often suffer from impracticality in daily clinical use, including excessive cost, time constraints, and limited processing capabilities. **Summary:** This review aims to evaluate existing techniques for clustering patients with the same neurological disorder to assist clinicians in optimizing treatment options. A narrative review of thirteen relevant studies was conducted, characterizing their methods, and evaluating them against seven criteria. Additionally, the results are summarized in two comprehensive tables. Recent approaches show promise; however, our results indicate that, overall, only three approaches display medium or high process maturity, and only two show high clinical applicability. **Key Messages:** Our findings highlight the necessity for advancements, specifically regarding the use of markerless optical tracking systems, the optimization of experimental

plans, and the external validation of results. This narrative review provides a comprehensive overview of existing clustering techniques, bridging the gap between instrumented gait analysis and its real-world clinical utility. We encourage researchers to use our findings and those from other medical fields to enhance clustering techniques for patients with neurological disorders, facilitating the identification of disparities within groups and their extent, ultimately improving patient outcomes.

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## Introduction

In an aging population, neurological disorders, specifically age-related illnesses such as Parkinson's disease or stroke, are gaining relevance. Within the EU, neurological disorders are already the third leading cause of disability and premature death [1]. As the patient population ages, developing more efficient and effective diagnostics and therapies becomes crucial. Both objectives can be facilitated through gait analysis (GA), specifically through technological solutions, commonly known as instrumented gait analysis (IGA). Despite its benefits,

application in clinical practice is limited due to high cost, time constraints, and limited processing capabilities.

Currently, gait is typically assessed using rating scales [2]. Manual assessments may raise concerns about interrater reliability, while computerized scoring could enhance objectivity, reliability, and ultimately validity, as standardized scales may miss key individual aspects. Several issues, however, impede the widespread use of IGA. Marker-based optical tracking systems, currently the gold standard for capturing gait, are both time-consuming and expensive. Although markerless systems are emerging, they still lag behind their marker-based counterparts [3, 4] (but show promise [5, 6]). Data processing remains problematic, as many solutions are only partially automated and impractical for daily clinical use. Furthermore, selecting appropriate features remains challenging, resulting in diverse approaches and limited evidence.

Existing reviews on IGA can be categorized into four groups: (1) reviews on the general state of IGA, presenting an overview of existing techniques and pathologies [7–9] or focusing on the efficacy of clinical IGA [10, 11]. (2) Analyses of the systems and sensors used in the field. While two studies [12, 13] provide a thorough description and review of current systems, most focus on wearable sensors [14–21]. (3) Studies addressing methodological and processing aspects [22–28], including the use of artificial intelligence [22–26]. (4) Reviews concentrating on subtopics, such as stroke [29], dementia [30], or children with cerebral palsy [31].

Despite numerous reviews, the topic of clustering in IGA is yet to be addressed. Clustering enables feature-based groupings of patients without predefined categories. It is, thus, well-suited for tasks like identifying subgroups in patients with the same disorder, facilitating tailored treatments for their specific needs. Since IGA can generate an abundance of patient data, combining it with clustering techniques holds promise for uncovering subtle differences. This study represents the first review of clustering approaches on IGA. Specifically, we address the following research question: Which clustering approaches were used to subgroup patients with the same neurological disorder, and along which criteria were subgroups formed?

In this paper, we evaluate thirteen approaches, some of which demonstrate valuable features that should be considered in future work applying clustering techniques to find subgroups within a group of neurological patients. Through our evaluation against seven criteria and presentation in two comprehensive tables, we offer valuable insights to researchers and practitioners seeking to improve the applicability of IGA in clinical practice.

## Methodology

### Terminology

According to the World Health Organization, neurological disorders encompass diseases of the central and peripheral nervous system [32]. Gait analysis (GA) refers to the study of human walking [8]. In this paper, we refer specifically to instrumented GA (IGA), which involves technological devices. Most of the studies reviewed rely on marker-based optical tracking systems (OTS), the gold standard in terms of accuracy, such as VICON<sup>1</sup> motion capture systems. They are contrasted by markerless OTS – which none of the studies used, however – which can extract gait patterns directly from images and video recordings. Additionally, floor sensors (e.g., force plates) or wearable sensors (e.g., inertial measuring units) can be used to capture gait data [12]. Generally, there are four types of GA data (cf. [7, 8]):

- Spatio-temporal: simple distance and time measurements, e.g., stride length.
  - Kinematic: measures of the motion of body segments, e.g., angular motion.
  - Kinetic: measures of forces, e.g., ground reaction forces (GRF).
  - Electromyographic: measures of muscle activity.
- Clustering is defined as the grouping of unlabeled data points [33].

### Survey

The inclusion criteria were as follows:

- The study applied IGA.
- The number of clusters was determined within the process.
- Patients had the same (consequence of a) neurological disorder.
- The IGA process, including the clustering, demonstrated a degree of automation.
- Studies worked with adults, as separate literature on children exists.

We conducted a narrative literature review, searching Google Scholar for articles fitting the inclusion criteria with combinations of search terms (clustering/subgrouping, gait/gait patterns/walking, disorder/stroke/hemiplegia/Parkinson/multiple sclerosis/ataxia/cerebral palsy). The bibliographies of the articles found were searched for additional matches, so were the studies citing the articles already included. We arrived at a concise set of thirteen papers. As comparison between approaches that cluster patients with the same neurological disorder does not exist, we describe and evaluate them in the following.

## Current Approaches – Overview

The approaches to cluster patients with the same neurological disorder will be presented in five groups. Note that we do not consider healthy controls or the clusters that emerged (almost) exclusively from healthy controls. A descriptive overview is given in Table 1.

<sup>1</sup>see here: <https://www.vicon.com>

**Table 1.** Descriptive overview with the most important information on each study

|                              | 2003               | 2008                  | 2014              |                   | 2016                       | 2017                   | 2018              | 2019            | 2020            | 2021                  | 2022                   |                 |          |
|------------------------------|--------------------|-----------------------|-------------------|-------------------|----------------------------|------------------------|-------------------|-----------------|-----------------|-----------------------|------------------------|-----------------|----------|
|                              | Mulroy et al. [34] | Kinsella & Moran [35] | Manca et al. [36] | Roche et al. [37] | Pauk & Minta-Bielecka [40] | Dolatabadi et al. [43] | Filli et al. [38] | Tan et al. [41] | Kim et al. [39] | Sekiguchi et al. [44] | Chantraine et al. [45] | Kim et al. [42] | Lee [46] |
| Clusters                     | 4                  | 3                     | 5                 | 5                 | 3                          | 2                      | 3                 | 3               | 4               | 3                     | 3                      | 6               | 3        |
| Participants                 | 47                 | 23                    | 49                | 44                | 41                         | 68                     | 37                | 30              | 88              | 72                    | 96                     | 36              | 50       |
| Disorder                     |                    |                       |                   |                   |                            |                        |                   |                 |                 |                       |                        |                 |          |
| Hierarchical Clustering      |                    |                       |                   |                   |                            |                        |                   |                 |                 |                       |                        |                 |          |
| Non-Hierarchical Clustering  |                    |                       |                   |                   | BC                         | GM                     |                   |                 |                 |                       | KM                     | KM              | KM       |
| <b>Data – Measurement</b>    |                    |                       |                   |                   |                            |                        |                   |                 |                 |                       |                        |                 |          |
| Spatio-Temporal              |                    |                       |                   |                   |                            |                        |                   |                 |                 |                       |                        |                 |          |
| Kinematic                    |                    |                       |                   |                   |                            |                        |                   |                 |                 |                       |                        |                 |          |
| Kinetic                      |                    |                       |                   |                   |                            |                        |                   |                 |                 |                       |                        |                 |          |
| Electromyographic            |                    |                       |                   |                   |                            |                        |                   |                 |                 |                       |                        |                 |          |
| <b>Data – Used for CA</b>    |                    |                       |                   |                   |                            |                        |                   |                 |                 |                       |                        |                 |          |
| Spatio-Temporal              |                    |                       |                   |                   |                            |                        |                   |                 |                 |                       |                        |                 |          |
| Kinematic                    |                    |                       |                   |                   |                            |                        |                   |                 |                 |                       |                        |                 |          |
| Kinetic                      |                    |                       |                   |                   |                            |                        |                   |                 |                 |                       |                        |                 |          |
| Electromyographic            |                    |                       |                   |                   |                            |                        |                   |                 |                 |                       |                        |                 |          |
| <b>Systems – Measurement</b> |                    |                       |                   |                   |                            |                        |                   |                 |                 |                       |                        |                 |          |
| Optical (3D, Marker-Based)   |                    |                       |                   |                   |                            |                        |                   |                 |                 |                       |                        |                 |          |
| Floor Sensors                |                    |                       |                   |                   |                            |                        |                   |                 |                 |                       |                        |                 |          |
| Wearable Sensors             |                    |                       |                   |                   |                            |                        |                   |                 |                 |                       |                        |                 |          |
| <b>Systems – Used for CA</b> |                    |                       |                   |                   |                            |                        |                   |                 |                 |                       |                        |                 |          |
| Optical (3D, Marker-Based)   |                    |                       |                   |                   |                            |                        |                   |                 |                 |                       |                        |                 |          |
| Floor Sensors                |                    |                       |                   |                   |                            |                        |                   |                 |                 |                       |                        |                 |          |
| Wearable Sensors             |                    |                       |                   |                   |                            |                        |                   |                 |                 |                       |                        |                 |          |

**Disorder:** ■ = Stroke & Hemiplegia, ■ = Other; **Clustering:** □ = Not Applied, □ = Applied; **Measurement:** □ = No Measurement, ■ = Measurement; **Used for CA:** □ = Not Used, ■ = Used; CA = Cluster Analysis; GM = Gaussian Mixture Model; BC = Bi-Clustering Algorithm KMB, KM = K-Means

### First Attempts

The four earliest studies [34–37] have patients walk a 10 m walkway and use many, primarily spatiotemporal and kinematic variables for clustering, with clustering outcomes heavily influenced by velocity. (1) The first study [34] analyzed data from 47 stroke patients on admission to rehabilitation and from 42 of them 6 months after their stroke. Data collection involved an OTS alongside a stride analysis system, electromyography (EMG), and a dynamometer. Nonhierarchical clustering

yielded four subgroups at each testing point, which were, additionally, determined by peak knee extension in mid-stance and peak dorsiflexion in swing on admission and knee extension in terminal stance and knee flexion in pre-swing 6 months later. (2) Gait data from 23 stroke survivors suffering from hemiplegia and equinus foot deformity were gathered with an OTS and force plates [35]. Twenty-four variables, including kinetic parameters, were analyzed through hierarchical cluster analysis (although seven variables were removed due to correlation),

**Table 2.** Evaluative overview scoring the studies along seven criteria

|                        | 2003               | 2008                  | 2014              |                   | 2016                       | 2017                   | 2018              | 2019            | 2020            | 2021                  | 2022                   |                 |          |
|------------------------|--------------------|-----------------------|-------------------|-------------------|----------------------------|------------------------|-------------------|-----------------|-----------------|-----------------------|------------------------|-----------------|----------|
|                        | Mulroy et al. [34] | Kinsella & Moran [35] | Manca et al. [36] | Roche et al. [37] | Pauk & Minta-Bielecka [40] | Dolatabadi et al. [43] | Filli et al. [38] | Tan et al. [41] | Kim et al. [39] | Sekiguchi et al. [44] | Chantraine et al. [45] | Kim et al. [42] | Lee [46] |
| Design                 |                    |                       |                   |                   |                            |                        |                   |                 |                 |                       |                        |                 |          |
| Theoretical Foundation |                    |                       |                   |                   |                            |                        |                   |                 |                 |                       |                        |                 |          |
| Parsimony              |                    |                       |                   |                   |                            |                        |                   |                 |                 |                       |                        |                 |          |
| Automation             |                    |                       |                   |                   |                            |                        |                   |                 |                 |                       |                        |                 |          |
| Ground Truth           |                    |                       |                   |                   |                            |                        |                   |                 |                 |                       |                        |                 |          |
| Clinical Applicability |                    |                       |                   |                   |                            |                        |                   |                 |                 |                       |                        |                 |          |
| Process Maturity       |                    |                       |                   |                   |                            |                        |                   |                 |                 |                       |                        |                 |          |

**Design:** ■ = Exploratory, ■ = Confirmatory; **Existence:** □ = Not Present, ■ = Partly Present, ■ = Present; **Level:** ■ = Low, ■ = Medium, ■ = High

resulting in three subgroups. (3) Another study [36] analyzed 49 hemiplegia patients with equinus foot deformity. Data were collected using an OTS. Hierarchical clustering with 38 input parameters revealed five clusters, summarized into three groups by velocity. Ankle variables primarily described cluster characteristics. (4) Data of 44 adults with cerebral palsy were analyzed with an OTS [37]. After the removal of eight correlated variables, hierarchical clustering with 35 input parameters revealed five clusters, summarized into three subgroups by velocity, with kinematic parameters required for cluster allocation.

*By-Products*

Clustering was incidental in two studies [38, 39]. (1) One research group [38] studied 37 multiple sclerosis patients walking on a treadmill at 50% maximum velocity and identified three different gait types (spastic-paretic, ataxia-like, and unstable) by hierarchical clustering using 28 spatiotemporal and kinematic features recorded with an OTS. (2) Another group [39] analyzed 88 Parkinson’s patients during a 6 m walk using four spatiotemporal parameters for clustering, measured by an OTS and force plates. Four subgroups emerged, mainly differentiated by gait hypokinesia and cadence.

*Experimental Approaches*

Three approaches [40–42] involved experimental methods. (1) Forty-one stroke survivors were analyzed during a 10 m walk using an OTS and force plates to evaluate the newly proposed bi-clustering algorithm KMB [40]. Lower limb kinetics were used for both hierarchical clustering and the KMB algorithm, revealing three (bi-) clusters best characterized by velocity. (2) To create a kinetic index (KI) based on surface EMG from four leg muscles, gait data of 30 stroke survivors performing a 5 m walk were analyzed [41]. Through hierarchical clustering, three groups emerged, comparable to clusters obtained with spatiotemporal and kinematic data and best described by velocity. (3) Different clustering methods were compared utilizing the gait data from 36 poststroke hemiplegia patients [42]. Data were measured with an OTS and a force plate on a 10 m walkway at eight time points. Thirty kinematic features were used with three clustering algorithms, of which K-means achieved the best fit, resulting in six clusters.

*Sensory Mat*

One study [43] utilized a 4 m sensory mat over which 68 stroke patients walked at up to four time points. Seven spatiotemporal characteristics were gathered and

clustered using a Gaussian Mixture Model. This resulted in two clusters determined by velocity, cadence, gait symmetry, and gait variability measures.

#### *Recent Attempts*

Three recent studies [44–46] are advanced in their methods, analyzed stroke survivors, and mostly rely on OTS and derived kinematic parameters. (1) Data from 72 patients suffering from quasi-joint stiffness were obtained on a 7 m walkway with an OTS and force plates [44]. Kinematics and kinetics of the lower extremities were used with hierarchical clustering, resulting in three groups with different proportions of the use and type of ankle foot orthosis (AFO). (2) In another study, 96 patients with unilateral stiff-knee gait (SKG) were optically tracked on a 10 m walkway [45]. K-means with five kinematic parameters led to five clusters of which three contained almost all patients (unbend-knee gait, braked-knee gait, frozen-limb gait). (3) An OTS and a force plate gathered data from 50 patients suffering from SKG and walking on a treadmill with self-selected speed [46]. A kernel K-means with three kinematic inputs was used to identify three clusters, mainly characterized by velocity, knee flexion, and propulsive asymmetry.

### **Current Approaches – Evaluation**

We evaluate existing approaches against seven criteria. We assess the studies' *design* choices as more exploratory or confirmatory in nature. Next, we apply four criteria to determine whether there exists a *theoretical foundation* for the variable choice and a *ground truth* evaluation and assess the level of *parsimony* and *automation* in the processes as low, medium, or high. Based on our findings, the last two criteria serve as overall scores. We rate the *clinical applicability* and *process maturity*, also as low, medium, or high. Our scoring system is based on a review using similar methodology [47]. An overview is provided in Table 2.

#### *Design*

*Exploratory* approaches typically investigate new phenomena, while *confirmatory* approaches validate existing hypotheses. *Confirmatory* studies require more theoretical evidence and, therefore, tend to be more advanced, while *exploratory* studies introduce new ideas. Most of the approaches considered are *exploratory*, with the majority using clustering to investigate the (aspect of the) disorder for the first time or expand knowledge about it [34–39, 46]. Conversely, two works [40, 41] explore new

methodologies, and another study [42] compares algorithms. Note that the methodological sophistication of the *exploratory* approaches varies considerably. The remaining three approaches have a more *confirmatory* nature. While one research group [43] primarily demonstrates the successful application of their approach in practice, two others [44, 45] construct classification systems grounded in existing knowledge.

#### *Theoretical Foundation*

A strong theoretical basis is crucial for interpreting clustering results accurately. Selecting variables based on a broad scientific rationale ensures that only necessary variables are chosen, thereby reducing noise. However, two studies fail to provide justification for their variable selection [34, 40]. Seven studies partially meet the criterion of a strong theoretical foundation but have a limited theoretical basis [35, 37], rely on theoretical without empirical support [36], or only offer theoretical background for some variables [43, 44]. Furthermore, justifications are sometimes broadly argued [38, 42, 44]. The remaining four studies furnish well-developed and specific theoretical background [39, 41, 45, 46]. Two approaches [45, 46] are particularly noteworthy since their theoretical derivations result in a limited selection of only kinematic parameters.

#### *Parsimony*

Related to the theoretical foundation is the concept of parsimony. It refers to preferring the simplest solution, which, here, means using as few input variables as possible. Like a good theoretical foundation, it reduces noise and allows for meaningful interpretation. We evaluate parsimony based on the number of input variables, but also on whether there is proper justification for the selection of numerous variables. For some studies, assessing parsimony proves difficult since the number of input parameters is not specified [34, 40, 44] or only for certain parts of the analysis [41]. Here, we had to estimate the number of parameters from the process description. Overall, we identify six studies exhibiting *low* parsimony. While, for most [36–38, 42], this is based primarily on the number of input parameters, the exclusion of input variables due to high correlation with other inputs is also considered [35, 37]. Four studies were assigned a *medium* parsimony. Although it is difficult to evaluate the exact set of input variables [34, 40, 41, 44], they are selective in terms of their inputs, qualifying them for their rating. With only four input parameters, the KI [41] could qualify for a higher score. However, we assigned a *medium* rating because it is challenging to determine the number of variables used for the overall clustering, which

does not appear excessively selective. Four approaches [39, 43, 45, 46] score *high* for parsimony, using a single-digit number of input parameters. The same approaches standing out for their theoretical foundation [45, 46] are, again, noteworthy for arriving at a concise set of kinematics.

#### *Automation*

Efficient clustering solutions rely on automation to save time and resources. While a level of automation was required to meet the inclusion criteria, some studies involve manual work, such as removing correlated input variables [35, 37] or detecting toe-off and heel strike to define the gait cycle [41, 45]. Furthermore, the KMB algorithm [40] requires manual parameter settings. Therefore, these solutions receive a *medium* rating. All other approaches, based on their procedural descriptions, do not require any more manual work but what can be considered standard tasks (selection and transformation of input variables, definition of criteria for the number of clusters, outlier removal, and implementation of the clustering algorithm). Therefore, we rate their automation as *high*.

#### *Ground Truth*

Assessment of ground truth, i.e., comparison of cluster results with an established clinical rating, is essential for clinical meaningfulness. However, only six of the thirteen studies reviewed performed such comparisons. The most common ground truth was a clinical assessment (i.e., a clinical rating scale or test) [38, 43–45], of which all but one study [44] used two. Another type of ground truth was a standard walking test, such as the 25-foot and the 6-min walk test [38], or the Timed Up and Go test [41] (only used for the KI but not for the standard procedure). Only one study [46] used expert judgment. The expert had to judge whether patients had SKG based on reconstructed animated videos. Although one study [38] employed four ground truth measures, none matched their cluster solution. Two approaches achieved mixed results [43, 44], while the other three achieved good agreement with their ground truths [41, 45, 46]. However, two of these studies [41, 46] used only one ground truth.

#### *Clinical Applicability*

The aim of GA research should be good clinical applicability, ensuring that the approach is feasible and beneficial in a daily clinical setting. However, of all the studies reviewed, only two [41, 43] demonstrate *high* clinical applicability since the other studies utilized marker-based OTS, which are impractical for everyday clinical use due to time constraints [48, 49]. The solutions

that we consider having *medium* clinical applicability have practically beneficial aspects. Two studies [45, 46] offer theoretically sound, parsimonious solutions which are valuable if marker-based systems are feasible. Additionally, a classification system for ankle-foot orthoses [44] was developed that may have practical use. All other studies have *low* clinical applicability due to theoretical imprecisions, broad variable selection, inefficient system usage, or their experimental nature. While some of these approaches may hold future potential, the solutions presented are not sufficiently advanced.

#### *Process Maturity*

We, finally, evaluate how far studies have progressed towards practical solutions that exploit the potential of IGA. Two studies [45, 46] exhibit considerable sophistication, creating theoretically sound and concise solutions based on kinematic data. Minor enhancements, such as increased automation [45] and incorporation of clinical assessment [46], could further improve their quality. Of course, both approaches would ideally use markerless systems to enhance their clinical applicability. Otherwise, they can be regarded as blueprints. We, therefore, give them a *high* rating. The one approach with a *medium* rating [44] produces helpful outcomes but experiences some inaccuracies regarding its theoretical foundation and parsimony that prevent it from receiving a high rating. Clarification of processes and the utilization of markerless systems hold great promise. All other approaches currently have *low* process maturity, but for very different reasons. One approach [43] is clinically applicable and parsimonious but does not exploit the potential of IGA using only spatiotemporal data. The KI [41] may hold future value but needs further validation. The same applies to the KMB algorithm [40], although this experimental approach seems less promising. Another study [42] could be a good starting point for future research, although it needs theoretical clarifications and a more precise choice of algorithms and input variables. In contrast, clustering was a by-product for two research groups, resulting in imperfect approaches [38, 39]. The four earliest studies [34–37] are limited by their status as pioneering works, as they lack prior research, have limited theoretical foundations, and employ overly broad choices of variables.

## **Conclusion**

As numerous studies suggest, an improved and more applicable version of IGA has the potential to significantly advance the diagnosis and treatment for multiple

diseases (cf. [7, 9, 11, 13, 21]), even in their early stages [50, 51]. However, high cost, time constraints, and lacking processing solutions limit its widespread clinical use.

This narrative review examines clustering approaches for patients with the same neurological disorder and provides two comparative tables. A successful implementation of clustering would allow practitioners to differentiate patient groups or identify groups with comparable attributes to that of an individual patient, facilitating personalized treatment and therapy. We identify the methods used for SKG patients [45, 46] as the most advanced and see potential in the AFO classification system [44]. Furthermore, we observe a high clinical applicability for the sensory mat approach [43], which is, however, very basic using solely spatiotemporal parameters, and the wearables-based KI [41], which requires further validation. All other approaches are not advanced enough to be used in clinical practice or to guide future research.

As the first review of existing approaches, we aimed to show the evolution of the field and guide future research. However, there are limitations as we only considered studies that met the inclusion criteria, which means that we did not include other approaches used in, e.g., classification studies that could be applied to clustering designs. Nevertheless, this study serves as a starting point for researchers and practitioners who wish to further develop the process of GA.

Our review shows that, currently, no clinically applicable, highly mature approach exists. Most importantly, dependence on marker-based OTS is a major obstacle for clinical practice. Recent research shows [5, 6], it is becoming possible to obtain good data using markerless systems. There is also a need for more confirmatory approaches. Although not better in general, they are needed to take advantage of the knowledge gained so far and to develop more complex solutions such as classification systems [44, 45]. Moreover, it is crucial for future studies to evaluate their findings in the context of the subgroups identified in recently published large-scale research from more conventional fields than gait analysis (cf. [52–54]). These discoveries should also be used to select appropriate features as inputs for clustering. Additionally, collaboration with research initiatives such as MOBILISE-D<sup>2</sup>, a project aimed at developing a comprehensive system for mobility analysis in daily life using wearable sensors, could be promising for combining real-world measurements with classical gait analysis and to gain perspectives on mobility changes over time. Fur-

thermore, establishing standardized protocols for GA and data collection may be beneficial. Finally, clusters are, usually, determined by velocity. Setting a constant velocity, although potentially unsuitable for certain patients, may provide valuable insight into the importance of other variables.

This review comprehensively analyzes approaches using IGA to cluster patients with the same neurological disorder. Most approaches are, currently, not ready for immediate clinical use; however, recent research shows promise [44–46]. The results of our work serve as an important steppingstone for researchers and practitioners to consider the current state of the art and progress toward improved diagnosis and treatment of patients.

### Conflict of Interest Statement

Manuel Stein and Daniel Seebacher are with Subsequent GmbH, which focuses on the development of highly accurate, real-time optical tracking systems based on markerless pose (skeleton) detection and visual-interactive motion analysis in various application areas. The other authors have no conflict of interest to declare.

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### Author Contributions

Jonas Hummel served as the primary author of the paper, making significant contributions to the conceptualization, research execution, data analysis, and manuscript composition. Additionally, he played a crucial role in developing the classification schema for the papers, which served as the foundation for structuring and assessing the studies. Michael Schwenk and Manuel Stein contributed significantly to the initiation of the research project, providing the initial idea for the paper and assisting in defining its structure, content, and framework. Daniel Seebacher was involved in the writing, elaboration, and refinement of the paper, contributing to its overall development. Philipp Barzyk and Joachim Liepert acted as expert advisors, making vital contributions to ensuring the paper's scientific quality and relevance. They provided valuable insights and guidance throughout the research process. All authors actively participated in reviewing and editing the manuscript to ensure the quality and accuracy of the final content.

<sup>2</sup> see here: <https://www.imi.europa.eu/projects-results/project-factsheets/mobilise-d>

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