A Concept for Daily Assessments During Nutrition Intake: Integrating Technology in the Nursing Process

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Abstract: The nursing process involves a cyclic sequence of functional and cognitive assessments and diagnosis, care planning, implementation, and evaluation of care. Ideally, this process should be performed regularly and documented in a standardized nursing language. However, due to the high workload of nurses, this approach is not systematically followed. Therefore, we developed a concept that enables a daily, technology-supported assessment during the activity of nutrition intake. For this purpose, we used camera-based body tracking to derive the hand and relevant object trajectories to analyze the movements regarding assistance needs and functional changes over time. We tested the approach of using generative AI to create training data sets. Our feasibility study has shown that trajectories can be derived and analyzed regarding assistance requirements. Although the quality is not yet satisfactory, generative AI can be used to create training data. Considering the rapid pace of further developments in generative AI, the approach seems to be promising. In conclusion, we believe that the technical support and documentation of the nursing process have the potential to increase the quality of care while reducing the workload of nurses.

1 INTRODUCTION

Due to the demographic change, the number of people reaching old age increases. This development will also result in an increasing demand for health and care services. The number of people in need of care in Germany will increase by 37% by 2055 due to ageing alone (Statistisches Bundesamt (Destatis), 2023). There is already a gap between the supply of carers and the demand for care. Additionally, it was shown that the patient-to-caregiver ratio has measurable negative effects on patient mortality rates and the stress experienced by caregivers (Höhmann et al., 2016; Aiken et al., 2012).

To realize qualified, patient-centered, and needs-based care, the nursing process was established, which is a systematic approach to organizing nursing practice, nursing knowledge, and nursing care (Hojdelewicz, 2021; Doenges and Moorhouse, 2012).

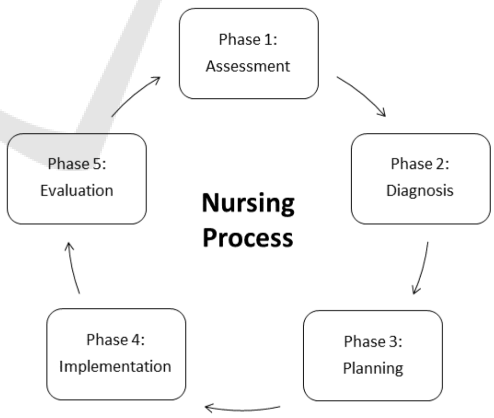

Figure 1: Five phases of the nursing process.

The five-phases model of the nursing process (Doenges and Moorhouse, 2012) is shown in Figure 1 and starts with an assessment to collect information about the patient, the diseases, and the functional status. In phase two a diagnosis is made on the basis of the assessment results. Phase three is the treatment and care planning. The treatments and nursing actions are im-

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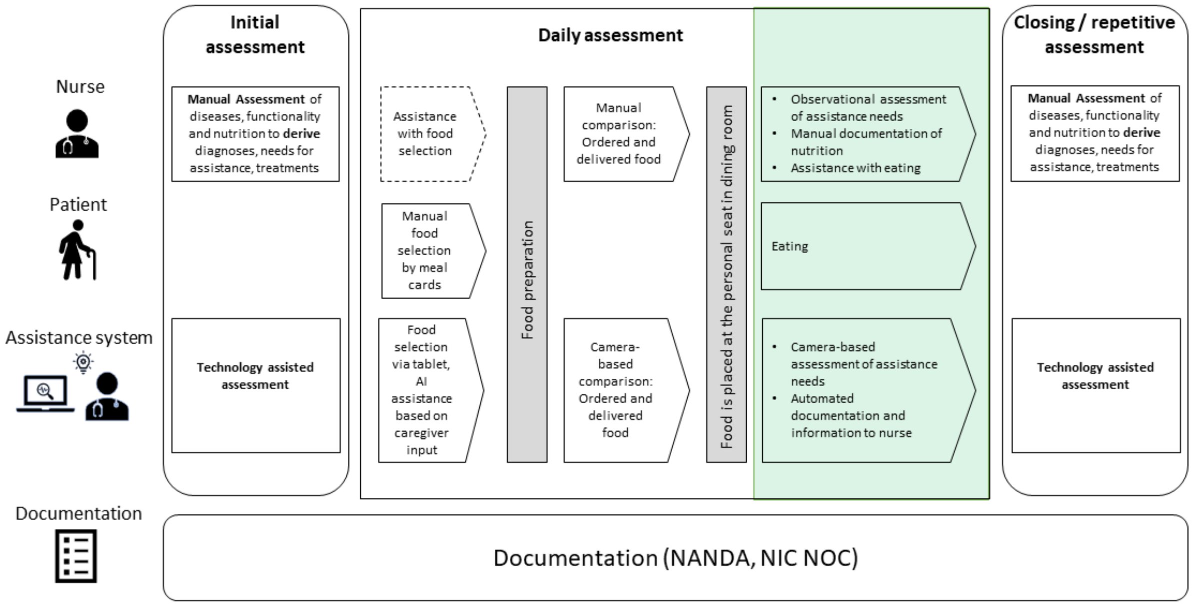

Figure 2: Assessment phases in a care process should be performed regularly. They can be done manually by a nurse or technology assisted by an assistance system. The focus of this paper is to assess the activity of eating (green box).

plemented in phase four and evaluated in phase five. Since the care process is of continuous nature, it starts again with phase one.

Due to the high workload of nurses, there is often a lack of time to implement the nursing process regularly at short intervals and, above all, to document nursing care adequately. The use of a standardized nursing language is particularly important for the implementation of electronic health records (EHR) (Lunney, 2006). Standardized nursing language includes NANDA (Ackley and Ladwig, 2010) for nursing diagnoses, the Nursing Interventions Classification (NIC) (Bulechek et al., 2012), which describes the activities that nurses perform as a part of the planning phase and the Nursing Outcomes Classification (NOC) (Moorhead et al., 2023) to evaluate the effects of nursing care.

Ongoing technological development is increasingly finding its way into the care sector and can support nurses in their daily work. There are already a number of approaches to technology-assisted assessments (Hellmers, 2021), technical systems to reduce the physical strain on nurses (Brinkmann et al., 2022), and applications of extended reality (XR) in the care context (Carroll et al., 2020; Wüller et al., 2019). Artificial intelligence (AI) in nursing is mainly used for early disease detection and clinical decision making, support systems for patient monitoring and workfow optimisation, nursing training and education (Martinez-Ortigosa et al., 2023). Newer developments such as generative AI (GenAI) also offer interesting possibilities, as they are able to generate synthetic data, which can be used to augment training data and create diverse datasets for research and medical training (Lancet Regional Health-Europe, 2023). Therefore, we will focus in this article on a holistic approach to the technical support of the care process, considering the application of GenAI. Figure 2 shows the assessment phase of the care process and the actions of the nurse, the patient, and the assistance system in this phase. This article focuses on the daily assessment (green box). However, an initial assessment is performed upon admission to a care facility to determine the patient's functional status, identify any assistance needed, and plan care. For short-time stays a closing assessment is usually performed before discharge to determine the success of treatment. For longer stays, the assessment should be repeated regularly as part of the repetitive care process. The assessments can be done manually by a nurse or technology-assisted.

High frequent assessments can also be realized by monitoring and analyzing daily activities like nutrition intake. Inadequate nutritional and hydration status in older people with healthcare needs has relevant negative effects on the immune system, cognitive function, and physical mobility. It is also a risk factor for susceptibility to infection, delayed wound healing, falls, delirium, altered metabolism of medications, deterioration of physical and cognitive function, and other adverse reactions (Volkert et al., 2022; Feldblum et al., 2009). The high relevance of nutrition and hydration for maintaining functional status, autonomy, and quality of life (Volkert et al., 2022) is a major motivation for this work.

The food selection is often done by the patients via meal cards and can be assisted by nurses if necessary. Technological systems can also assist the patient with the food selection based on the individual nurses' input for each patient. After food preparation, the nurses check if the ordered and delivered food matches. This comparison is relevant for disease-specific diets, allergies, or if the patient can only eat soft food. Object recognition by assistance systems can also be used for this comparison. Since the food intake is at focus in this paper (green box in Figure 2), the phase of eating is relevant to derive requirements for assistance needs and changes in the functional status. The assessment can be conducted through observation and manual documentation by a nurse. This observational assessment can also be supported by a camera-based assessment, in which the assistance systems derive assistance needs and functional changes based on activity recognition and the analysis of the activities, for example, the hand trajectories while eating. The results can be automatically documented in a standardized language (NANDA, NIC, NOC). In this case, the nurses can screen the information and plan the nursing care regarding the nursing process.

In summary, we concentrate on the overall concept of a technology-assisted daily assessment using new technological developments and focus on the following research questions:

- What can a high frequent assessment look like in which the caregiver and the assistance system support each other in a meaningful way?
- How can new technological developments such as generative AI be used?
- How can a standardized care language be implemented in this concept?

2 METHODS

2.1 Concept of Daily Assessments

One point of criticism of monitored assessments is that they only represent selective measurements and often no progressions are recorded. The aim is therefore to derive care-relevant assessment parameters from complex everyday activities. To do this, complex activities must first be recognized and relevant parameters derived on the basis of their performance. Deficits in self-care result for example from lack of hand functionality and coordination skills. For sensory recognition of activities, aspects such as contextualization and parallelism must be taken into account (actions have a certain duration and sequence and may also involve interaction with objects). The digital information should be collected uniformly and documented in a standardized language. Nursing professionals assess information collected through technology, extend it by own observations, and may utilize a decision support system in the future to determine and implement practical interventions for nutrition and hydration. With regard to activating care, nursing interventions are also examined in order to derive and document suitable strategies for food and fluid intake. Based on the successful strategies, self-help can be supported in a targeted manner and the care staff can be relieved.

2.2 AI-Generated Norm-Trajectories and Real Measurements

As a specific use case we concentrated on eating soup in this paper, since holding and moving a spoon without spilling can be quite challenging for people with functional disabilities. Three study participants took part in the study to demonstrate the feasibility of our concept. We used the RGB-D-camera Azure Kinect DK and its Azure Kinect Body Tracking SDK with the Direct ML processing mode. The trajectories of the right hand, right wrist, and right hand tip were calculated. Since the mouth can't be tracked with the Azure Kinect Body Tracking SDK we calculated the trajectories of the key points head and nose. The trajectories were filtered with a first-order Butterworth filter with a cutoff frequency of 5 Hz to reduce noise. We also generated AI-based videos with the RunwayML Gen-2 text-to-video tool (RunwayML, 2023) using the prompt: "Old man is sitting at a table and eats soup. He holds a spoon in the right hand". We performed a manual body and object tracking of the AI-generated videos. However, machine learning solutions like MediaPipe (Lugaresi et al., 2019) can be used for automatic tracking.

3 RESULTS

3.1 Concept of Daily Assessment

Figure 3 shows the concept of a camera-based technology-supported assessment. The main aspect of realizing such an assessment is the recognition of the human and the food. Therefore, body tracking is used to recognize the position of the mouth and the hand. Object recognition is used to determine the po-

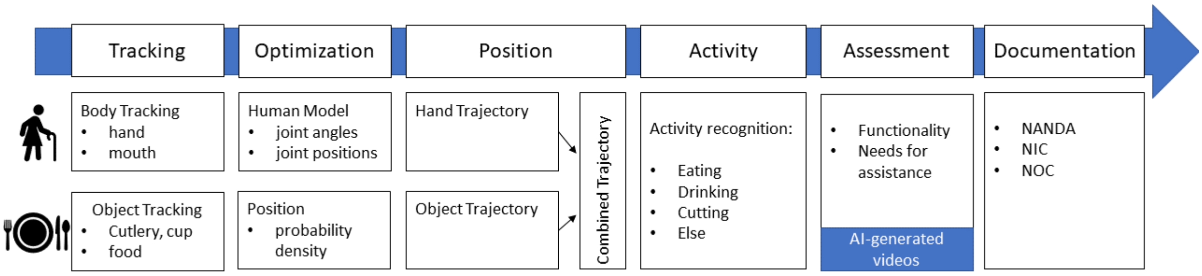

Figure 3: Technical process of activity recognition and assessment.

Figure 4: Screenshots of an AI-generated video of an old man eating soup (RunwayML, 2023).

sition of the food and other relevant objects like cutlery or cups. For optimization of the body tracking a human body model should be considered. This model consists of valid joint angles and relative positions so that unrealistic positions are automatically removed. For objects a position probability density should be considered, to remove outliers and unrealistic positions as well as the problem of suddenly disappearing objects for example due to occlusions. Based on the optimized body tracking results the hand and object trajectories can be calculated and related to each other to get a combined trajectory. Analyzing the combined trajectories leads to activity recognition. Machine learning based methods for activity recognition can be divided into two categories: Direct classification and sequential modeling (Poppe, 2010). When the temporal sequence of an activity is important, sequential models are required to represent this sequence in the form of state models. Eating and drinking correspond to a sequential activity: the glass must first be grasped, then brought to the mouth and tilted slightly in order to drink. Then the glass is put down again. In the next step the activity can be analyzed and assessed regarding functional and assistance needs. A focus of inquiry could be the shapes of the trajectories (intentional movement, movement disorders such as tremors) and the effectiveness of food consumption, exemplified by the ability to hold and use cutlery successfully.

Machine learning approaches often require a huge set of training data of normal and pathological activities. The ongoing development of generative AI might be a game changer in this field. We proved the concept of using AI-generated videos to create training data. Since the AI models are trained on many videos mostly without pathological findings, these videos are used as norm trajectories. The last step includes the documentation of the assessment with a standardized nursing language.

3.2 AI Generated Norm-Trajectories

We created AI-generated videos with textual input. Figure 4 shows three screenshots of one video. This video fits the description very well. From the patient information (old man) and the delivered food (soup) as well as the context (eating food while sitting at the table), the correct objects (bowl, spoon) as well as the correct trajectories (spoon to mouth) and hand orientations (horizontal posture) are derived. However, there are also some contextual errors or curiosities. For example, the man is also holding a second plate of soup in his left hand. The manual body and object tracking is shown in Figure 5. The trajectories of the mouth (green), the knuckles (blue), and the tip of the spoon (orange) are visualized. The man sits in a slightly bent posture during the video. There is almost no movement of the upper body and the head. Therefore, the position of the mouth varies only in a small range. The trajectory of the hand starts with an arc to fill the spoon with soup, followed by a direct trajectory to the mouth. The video stops before the spoon

Figure 5: Manual tracking of mouth, knuckles, and spoon in the AI-generated video (RunwayML, 2023).

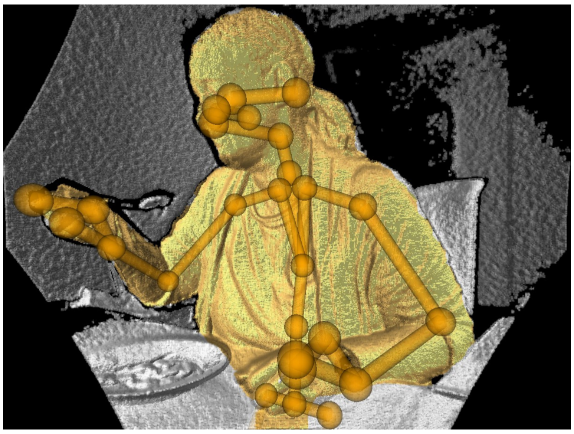

Figure 6: Body tracking of a real measurement of a person eating with a spoon.

reaches the mouth. The measurement of the trajectory of the spoon (orange) is interrupted quite extensively due to the disappearance of the spoon in the middle of the video. The presented video is one of the best-fitting videos. The challenges and further observations in generating AI-based videos are described in the discussion section 4. However, the feasibility of using generative AI to create training data for activity recognition could be confirmed. A selection of some further videos with similar textual prompts as input is uploaded here (AI-generated Videos, 2023).

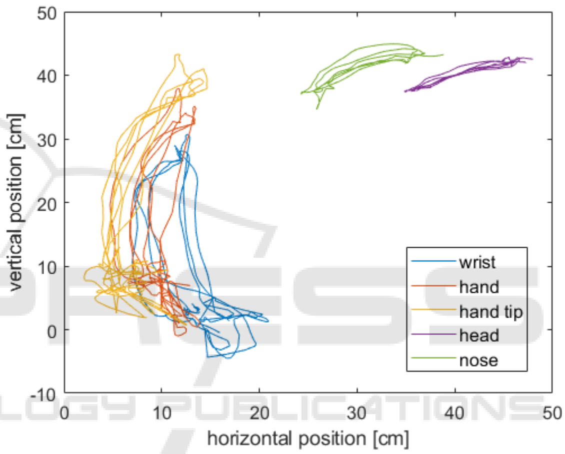

Figure 7: Trajectories of relevant key points of a person eating with a spoon.

3.3 Measurement of Real Trajectories

Figure 6 shows the body tracking results of one participant based on depth data using the Azure Kinect SDK. Similar to the tracking in the AI-generated video, the trajectories of the relevant key points were recorded and presented in Figure 7. For the right hand, the key points are the wrist, the hand itself as well as the hand tip. Since the mouth can't be tracked with the Azure Kinect SDK, the key points head and nose are visualized. For better comparison and interpretation of the trajectories with the video screenshot in Figure 6, a 2D representation was chosen. However, the positions of the key points are available in 3D so that the perspective can be adjusted. The trajectories for three cycles (spoon to mouth) are shown. The trajectories are similar for each cycle. The hand position is stable while bringing the spoon to the mouth. The head is moved in the direction of the spoon.

Figure 8 shows the trajectories of the same person while eating with a fork. The trajectories differ from eating with a spoon. There is a 90-degree tilt of the hand while using a fork. It can also be seen that the head movement varies in a smaller range than while

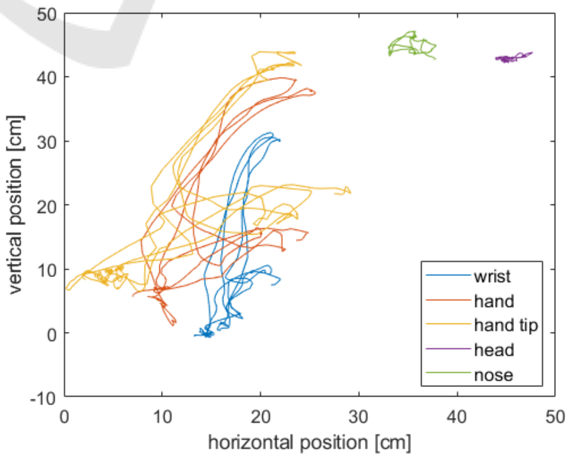

Figure 8: Trajectories of relevant key points of a person eating with a fork.

eating with a spoon. Comparisons with trajectories of the other study participants (not shown here) indicate that each person has an individual trajectory, but the trajectories stay similar during several cycles.

3.4 Documentation

The use of a standardized nursing language in daily work and communication is particularly important for the care of patients and those in need of care between the various actors in health and nursing care (Bernhart-Just et al., 2010).

The nursing diagnosis, which can be derived from the presented daily assessment is ”feeding self-care deficit”, which includes for example the inability to bring food to mouth, get food onto utensils, handle utensils, open containers, pick up a cup or a glass (Wilkinson, 2014; Herdman et al., 2021). These inabilities can be derived from the evaluated videos and the object and hand trajectories. Consider the example of eating soup: If, for example, the trajectory for eating soup is similar to the trajectory of the (AI-) generated norm trajectories, no deficit in eating is coded. However, if the trajectory deviates from the norm trajectories, inabilities such as bringing food to the mouth or handling utensils can be assumed. In this case, a feeding deficit is documented.

A relevant NOC outcome for these patients is ”Self-Care: Eating”, which is related to the patient’s ability to prepare and ingest food and fluid independently with or without assistive device. Relevant NIC interventions include ”Feeding” for a patient who is unable to feed him- or herself, or ”Self-Care Assistance: Feeding,” which means assisting a person to eat. ”Nutrition monitoring” as another intervention involves the collection and analysis of patient data to prevent or minimize malnutrition (Wilkinson, 2014). Nursing activities also include ”Eating Techniques Instruction” to demonstrate the proper use of utensils, assistive devices, and adaptive activities to teach patients alternative methods of eating and drinking.

4 DISCUSSION

We developed a concept that enables a daily, technology-supported assessment during the activity of nutrition intake. For this purpose, we used camera-based body tracking to derive the hand and relevant object trajectories to analyze the movements regarding assistance needs and functional changes over time. Additionally, we tested the feasibility of using generative AI to create training data sets.

We were able to demonstrate the general implementation of the assessment concept in this paper in a pilot study, although only the nursing diagnosis of feeding self-care deficit can be included. Other nutrition-relevant nursing diagnoses like frailty syndrome, unbalanced diet, impaired swallowing, fluid imbalance, and inadequate fluid intake have yet not been considered. Especially, the feasibility of assessing the diagnosis of impaired swallowing and the unbalanced diet could be realized in the next step via video analyses and digital before and after plate protocols.

Generative AI seems to be a promising approach to creating training data, especially when considering the high pace of further developments. We expect that the quality of AI-generated videos by the text-to-video function will highly increase in the next years. This enables the possibility to generate training data sets without involving and burdening patients. It holds also the possibility to generate videos with patients with specific symptoms like tremors or paralysis in the future. However, in addition to the still poor match between text input and generated videos, and contextual or physical errors or abnormalities (second cup of soup, oversized spoon, spoon disappears or seems to melt), we also observed ethical issues. The videos with an ”old person” as input often generated a clichéd video background with dark old wooden furniture. Stereotypes are also used, e.g. by generating videos where instead of a woman eating soup, an old woman spills the soup and it runs down her chin. This also shows the dangers of artificial intelligence in terms of prejudice and stigmatization. Therefore, synthetically generated data should be used with caution and it is important to bear in mind that the expertise of care professionals is required for the meaningful training of AI and the integration of meaningful data. This is particularly important if the AI is to take over clinical pathways, disease progression, or the prediction of deterioration and thus prepare the ground for professional action for example in clinical decision support systems. According to the literature, IT- and AI-based processes in nursing can support clinical decisions or even generate automatic warning systems and thus also systematically support the nursing workflow and enable personalized patient care (Sensmeier, 2017; Buchanan et al., 2020). But new technologies in nursing influence the interaction between the actors (caregivers and care recipients), the organizational processes in the nursing setting, and the associated information relationships between the actor (Zerth et al., 2021). Therefore, we suggest that decisions need to be made with the actors, especially the nurses, about what data needs to be collected and integrated, for what reasons, and with what purpose, so that it is adequate for the care process and decision-making.

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REFERENCES

Ackley, B. J. and Ladwig, G. B. (2010). *Nursing diagnosis handbook-e-book: An evidence-based guide to planning care*. Elsevier Health Sciences.

AI-generated Videos (2023). https://cloud.uol.de/s/bKcKGy3QKG7LdEm.

Aiken, L. H., Sermeus, W., Van den Heede, K., Sloane, D. M., Busse, R., McKee, M., Bruyneel, L., Rafferty, A. M., Griffiths, P., Moreno-Casbas, M. T., et al. (2012). Patient safety, satisfaction, and quality of hospital care: cross sectional surveys of nurses and patients in 12 countries in europe and the united states. *BMJ*, 344:e1717.

Bernhart-Just, A., Lassen, B., and Schwendimann, R. (2010). Representing the nursing process with nursing terminologies in electronic medical record systems: a swiss approach. *CIN: Computers, Informatics, Nursing*, 28(6):345–352.

Brinkmann, A., Böhlen, C. F.-v., Kowalski, C., Lau, S., Meyer, O., Diekmann, R., and Hein, A. (2022). Providing physical relief for nurses by collaborative robotics. *Scientific Reports*, 12(1):8644.

Buchanan, C., Howitt, M. L., Wilson, R., Booth, R. G., Risling, T., and Bamford, M. (2020). Predicted influences of artificial intelligence on the domains of nursing: scoping review. *JMIR nursing*, 3(1):e23939.

Bulechek, G. M., Butcher, H. K., Dochterman, J. M. M., and Wagner, C. (2012). *Nursing interventions classification (NIC)*. Elsevier Health Sciences.

Carroll, W. M. et al. (2020). *Emerging technologies for nurses: Implications for practice*. Springer Publishing Company.

Doenges, M. E. and Moorhouse, M. F. (2012). *Application of nursing process and nursing diagnosis: an interactive text for diagnostic reasoning*. FA Davis.

Feldblum, I., German, L., Bilenko, N., Shahar, A., Enten, R., Greenberg, D., Harman, I., Castel, H., and Shahar, D. R. (2009). Nutritional risk and health care use before and after an acute hospitalization among the elderly. *Nutrition*, 25(4):415–420.

Hellmers, S. (2021). *Technikgestütztes klinisches Assessment der körperlichen Funktionalität für ältere Menschen*. Verlag Dr. Hut.

Herdman, T. H., Kamitsuru, S., and Lopes, C. (2021). *NANDA International Nursing Diagnoses: Definitions and Classification 2021-2023*. New York: Thieme, 12th edition.

Höhmann, U., Lautenschläger, M., and Schwarz, L. (2016). Belastungen im pflegeberuf: Bedingungsfaktoren, folgen und desiderate. *Pflege-Report*, pages 73–89.

Hojdelewicz, B. M. (2021). *Der Pflegeprozess: Prozesshafte Pflegebeziehung*. Wien: facultas.

Lancet Regional Health-Europe, T. (2023). Embracing generative ai in health care. *The Lancet Regional Health-Europe*, 30.

Lugaresi, C., Tang, J., Nash, H., McClanahan, C., Uboweja, E., Hays, M., Zhang, F., Chang, C.-L., Yong, M., Lee, J., et al. (2019). Mediapipe: A framework for perceiving and processing reality. In *Third workshop on computer vision for AR/VR at IEEE computer vision and pattern recognition (CVPR)*, volume 2019.

Lunney, M. (2006). Helping nurses use nanda, noc, and nic: Novice to expert. *JONA: The Journal of Nursing Administration*, 36(3):118–125.

Martinez-Ortigosa, A., Martinez-Granados, A., Gil-Hernández, E., Rodriguez-Arrastia, M., Ropero-Padilla, C., Roman, P., et al. (2023). Applications of artificial intelligence in nursing care: A systematic review. *Journal of Nursing Management*, 2023.

Moorhead, S., Swanson, E., and Johnson, M. (2023). *Nursing Outcomes Classification (NOC)-e-book: Measurement of health outcomes*. Elsevier Health Sciences.

Poppe, R. (2010). A survey on vision-based human action recognition. *Image and vision computing*, 28(6):976–990.

RunwayML (2023). `https://runwayml.com`. accessed: 2023-11-15.

Sensmeier, J. (2017). Harnessing the power of artificial intelligence. *Nursing management*, 48(11):14–19.

Statistisches Bundesamt (Destatis) (2023). Pflegevorausberechnung: 1,8 millionen mehr pflegebedürftige bis zum jahr 2055 zu erwarten. Pressemitteilung Nr. 124 vom 30. März 2023, https://www.destatis.de/DE/Presse/Pressemitteilungen/2023/03/PD23_124_12.html.

Volkert, D., Beck, A. M., Cederholm, T., Cruz-Jentoft, A., Hooper, L., Kiesswetter, E., Maggio, M., Raynaud-Simon, A., Sieber, C., Sobotka, L., et al. (2022). Espen practical guideline: Clinical nutrition and hydration in geriatrics. *Clinical Nutrition*, 41(4):958–989.

Wilkinson, J. M. (2014). *Pearson nursing diagnosis handbook with NIC interventions and NOC outcomes*. Pearson.

Wüller, H., Behrens, J., Garthaus, M., Marquard, S., and Remmers, H. (2019). A scoping review of augmented reality in nursing. *BMC nursing*, 18(1):1–11.

Zerth, J., Jaensch, P., and Müller, S. (2021). Technik, pflegeinnovation und implementierungsbedingungen. In Jacobs, K., Kuhlmey, A., Greß, S., Klauber, J., and Schwinger, A., editors, *Pflege-Report 2021: Sicherstellung der Pflege: Bedarfslagen und Angebotsstrukturen*, pages 157–172, Berlin, Heidelberg. Springer Berlin Heidelberg.