substantial role in these side effects. Up to now, less is known about perceived injustice in cancer survivors. Furthermore, no cancer survivors' specific cut-off is available, making further research difficult.

Material and methods: This cross-sectional study assessed the Injustice Experience Questionnaire (IEQ), Numeric Pain Rating Scale (NPRS), Patient-Specific Complaints (PSC), Multidimensional Fatigue Index (MFI), and European Organization for Research and Treatment of Cancer Quality of Life Questionnaire-C30 (EORTC-QLQ-C30) in cancer survivors from the Netherlands. A clinically relevant cut-off score for cancer survivors was identified based on the 75th percentile of the distribution of the total IEQ scores. Univariate and multivariate regression analyses were performed to explore the relationship between personal characteristics (gender, age, type of cancer, treatment type) and cancer-related rehabilitation factors (pain intensity, daily activity, fatigue, health-related quality of life) with perceived injustice in cancer survivors.

Results: One hundred twenty-one cancer survivors were included from private physiotherapy practices across the Netherlands. A cut-off of ≥20 on the IEQ was identified for cancer survivors. In the univariate analyses, chemotherapy (B = 3.321 [0.346 to 6.295], p = 0.029) and all rehabilitation factors (i.e., NPRS (B = 0.863 [0.161 to 1.566], p = 0.016), PSC (B = 0.067 [0.008 to 0.127], p = 0.027), MFI (B = 0.204 [0.124 to 0.284], p < 0.001), and EORTC-QLQ-C30 (−0.167 [−0.252 to −0.083], p < 0.001)) were significantly associated with the total IEQ scores. However, no significant indirect associations were found for gender (B = 1.520 [−1.779 to 4.820], p = 0.363), age (B = −0.094 [−0.208 to 0.019], p = 0.103), or type of cancer (B = 3.982 [−1.226 to 9.190], p = 0.133) with total IEQ scores. The multivariate model included MFI, EORTC-QLQ-C30, NPRS, PSC, type of treatment, age, and cancer type (p < 0.20). Only MFI and age maintained a statistically significant direct association with PI, which were respectively B = 0.205 [0.125 to 0.018], p < 0.001 and B = −0.086 [−0.191 to 0.285], p < 0.001.

Conclusion: Perceived injustice might be a new cornerstone for cancer survivors. However, its knowledge is scarce and its association with personal characteristics and rehabilitation factors should further be examined through longitudinal studies in a larger population to explore causal relationships.

No conflict of interest.

161 (PB-074) Poster
Overview of patient preference sensitive attributes in eHealth interventions for breast cancer-related fatigue

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Background: One of the most disabling long-term effects after breast cancer is cancer-related fatigue (CRF). To prevent CRF from becoming chronic, it is important to start treatment against CRF timely. Fortunately, there are many evidence-based eHealth interventions. However, the effectiveness of these interventions varies per person, depending on patients' personality and preferences. The goal of this research is to create an overview of eHealth interventions for breast cancer patients with CRF and their attributes, with a focus on preference sensitive attributes. This overview can help in providing a more personalized treatment advice, thereby increasing the effectiveness on CRF.

Methods: With a scoping review, we searched systematically through Pubmed, Scopus and Web of Science for eHealth interventions. These eHealth interventions had to 1) be tested in a patient group including breast cancer patients and 2) measure the effect on CRF. Information was extracted on patient preference attributes like duration, intensity, contact with healthcare professionals, peer support, costs, content delivery and study results. Results were synthesized based on different categories of non-pharmacological interventions.

Results: We found 43 articles describing 35 interventions. Interventions were divided into five categories: physical activity, mind-body and psychological interventions, a combination of the previous or "other." Table 1 shows the variation in the attributes duration, intensity, contact with professionals and study results per category. Peer support was included in only seven interventions and in six interventions, information was given on potential

costs. Content was delivered in various ways: information was presented on websites and apps as video, audio and text and also as vignettes, quizzes and graphics.

Conclusion: We created an overview of eHealth interventions for breast cancer patients with CRF and their (preference sensitive) attributes. There was variation between (categories of) interventions, showing possibilities to personalize an intervention advice. The overview hopefully supports professionals in guiding patients to an intervention that fits their preferences, leading to an improved intervention outcome on CRF and improving the quality of life of patients.

Table 1: Overview of interventions and attributes related to patient preferences

Category	Duration	Intensity	Professional involvement	Studies with significant improvement
Physical activity (n = 5)	6 weeks–6 months	Tailored by user - 3 hours/week - 3 sessions/week	4/5	2/5
Mind-body (n = 7)	4–12 weeks, outlier of 20 weeks	Daily practice of exercises	2/7	4/7
Psychological (n = 13)	6 weeks–6 months	Weekly usage/at own pace, two exceptions: 4x/week and daily use	6/13	9/13
Other (n = 2)	6 months	Own pace - daily usage	2/2	1/2
Combination (n = 8)	8 weeks–6 months	Usage at own pace - once/twice per week - daily use	5/8	8/8

No conflict of interest.

162 (PB-075) Poster
Who is at risk of developing breast cancer-related fatigue – a prediction study

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Background: Cancer-related fatigue (CRF) is still experienced by 20% of the breast cancer patients ten years after diagnosis. Although there are interventions against CRF, they should be started on time to prevent CRF from becoming chronic. Therefore, it is important to identify patients at risk of developing CRF to subsequently monitor them actively. The goal of this study is to explore the possibility to determine the risk breast cancer patients have for developing CRF.

Methods: To assess the risk for CRF, the Dutch Primary Secondary Cancer Care Registry (PSCCR) was used. This registry consists of a part with patient reported outcomes (PSCCR-PROFIEL) and a link between data of General Practitioners (GPs) and the Netherlands Cancer Registry (PSCCR). Both have information on breast cancer patient, tumor and treatment characteristics and late effects. In PSCCR-PROFIEL, 23 input variables for 390 patients were available and the patient reported outcomes included the late effect fatigue (yes/no, n = 254). In PSCCR, 12,813 patients were included and GP visits for fatigue were extracted (n = 2224). Fifty-three input variables were used, including information on complaints before diagnosis. Missing data was imputed using Multiple Imputation by Chained Equations. Risk was predicted using machine learning comparing several models: Random Forest Classifier, Logistic Regression, Gaussian Naïve