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Differences In Adherence to A Cancer-Specific Exercise Program Between Clinical Provider Ereferral and Self-Referral

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Abstract

Background: Exercise programs have substantial benefits for cancer survivors, including improving physical function and quality of life. Exercise program referral and enrollment are critical to initial participation, but it is unclear whether referral sources impact cancer survivors' adherence or engagement with an exercise program. This study compared program adherence between provider electronically referred and self-referred participants, matched on demographic and medical characteristics.

Methods: Participants were referred to an 8-week videoconference cancer-exercise program by (a) electronic referral by an oncology provider (eReferral), or (b) self-referral via support groups, social media pages. Participants were matched on age, sex, cancer type and education. Exercise and discussion sessions attended were compared using independent t-tests and program completions and reasons for joining were explored.

Results: Both eReferral (N=8) and self-referred (N=8) participants were on average over 60 years of age, and mostly diagnosed with breast cancer. Exercise session attendance was lower for eReferral participants [t (16) = 0.381, p = 0.07], and there was no difference in discussion attendance between groups [t (16) =0.158, p=0.87]. Program completion was 6/8 for eReferral and 7/8 for self-referred participants.

Conclusion: Self-referred participants attended more exercise, but a similar number of discussion sessions as eReferral participants. Cancer survivors who self-refer may have greater motivation to engage in a cancer specific exercise program. Findings suggest that a clinic-based eReferral system can help cancer survivors enroll in a virtual exercise program but may need added support to facilitate exercise engagement.

Keywords: Exercise Oncology; Referral System; Oncology referral

Introduction

Cancer-specific exercise programs provide support for engaging in leisure time physical activity (i.e., aerobic and resistance exercise training) tailored to the needs of individuals living with and beyond cancer (i.e., cancer survivors). Cancer-specific exercise programs have been shown to be successful in increasing leisure time physical activity among cancer survivors, which is associated with improved physical and psychosocial well-being [1,2]. Despite the presence and availability of cancer-specific exercise programs, not all cancer survivors are aware of these resources and/or may experience barriers to enrolling in such programs. One avenue that has been suggested to increase enrollment in cancer-specific exercise programs is via oncology provider referrals [3,4]. Though initial program adoption, or enrollment, is an important first step, adherence to and engagement in these programs is integral for eliciting increases in physical activity and subsequent positive health benefits. Findings of the effects of oncology provider recommendations on exercise engagement are mixed; one previous study found that oncologist recommendation may increase exercise behavior in newly diagnosed breast cancer survivors [5,6]. whereas another found that an oncologist recommended exercise recommendation did not increase exercise participation level [5]. In addition to mixed findings on how oncologist recommendations impact exercise behavior, little information exists on how referral sources influence cancer survivors' engagement and adherence to cancer-specific exercise programs. A previous study found that two-thirds of oncologists reported referring patients to a community-based program [6]. but it is unclear how this type of referral might impact engagement in the program, particularly as compared to other types of referrals (e.g., family/friends, or self-referral). Prior research in health behaviors have shown mixed findings regarding associations between referral type and program engagement. For example, one trial delivering acceptance and commitment therapy for smoking cessation found engagement in treatment sessions did not differ between self-referred and clinically referred patients [7]. In contrast, another trial found that provider-referred patients were 21% less likely to engage in services offered by a Quitline compared to self-referred patients [8]. It is currently unknown how the source of referral is related to program adherence or engagement in cancer-specific exercise programs. Thus, the purpose of this study was to examine differences in attendance during a cancer-specific exercise program between oncology provider vs. self-referred participants.

Methods

This study was a secondary data analysis of participants enrolled in the Fitness Therapy for Cancer (Fit Cancer) program (https://www.chhs.colostate.edu/hes/outreach-and-engagement/fit-cancer) [9]. an 8-week cancer-specific exercise program delivered via videoconferencing software. The program consisted of group-based exercise sessions once per week, and three physical activity behavior change discussion sessions. Participants entered the program by either (a) electronic referral during clinic visits via oncology provider (e.g., oncology nurse, social worker, navigator) by entering participants cellphone and email-address into a secure healthcare system referral webform (eReferral), or (b) self-referral via support groups, social media pages, or word of mouth. eReferral and self-referred participants were matched on age, sex, education, and self-reported physical activity level. Program adherence/engagement was defined as the number of exercise and discussion sessions attended and compared between eReferral and self-referred participants using independent t-tests. Completion rate and reasons for joining the program were also explored using frequencies, but formal, statistical comparisons could not be made because of the small sample size.

Results

eReferral participants (N=8) were M=60.70±0.150 years old, 65% breast cancer, 50% college educated, and reported M=102.34±85.2 minutes per week of moderate to vigorous physical activity. Self-referred participants (N=8) were M=61.01±0.142 years old, 50% breast cancer, 40% college educated and reported M=108.54±82.0 minutes per week of moderate to vigorous physical activity. Exercise session attendance was lower in eReferral (M=6.8 ±1.13) vs. self-referred (M=7±1.06) [t (16) = 0.381, p = 0.07]. There was no difference in discussion session attendance between eReferral (M=2.9 ±.1) vs. self-referred (M=2.8 ±.125) participants [t (16) =0.158, p=0.87]. The program completion rate was 75.0% (n=6) for eReferral participants, and 87.5% (n=7) for self-referred participants. We found reasons for joining were high for being recommended by a healthcare provider and virtual delivery modality. Reasons for joining the program are shown in (Figure 1).

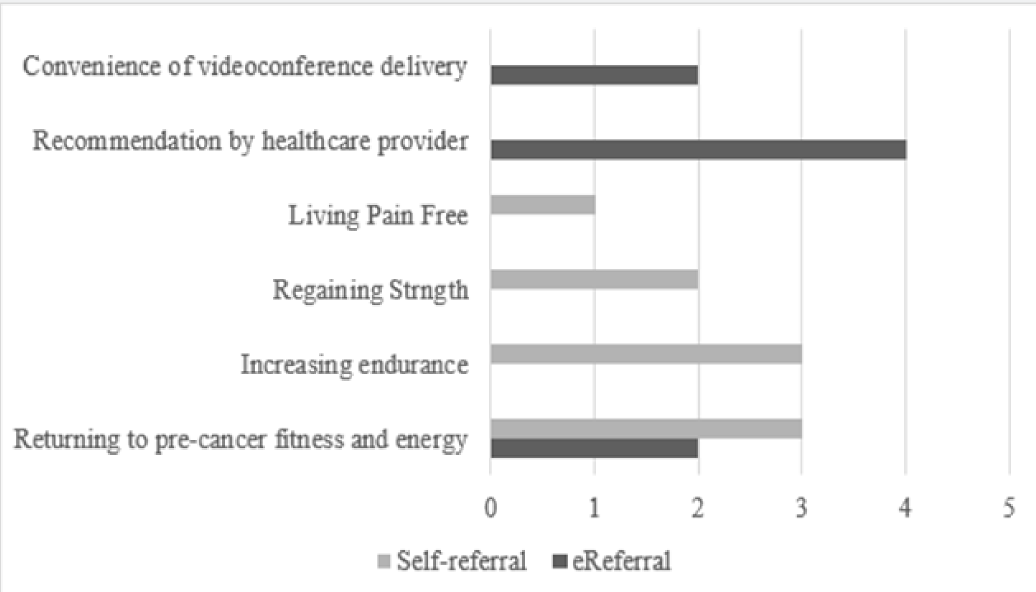

Figure 1: Reasons for Joining Fit Cancer Program.

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Discussion

This study found that self-referred participants attended more exercise, but a similar number of discussion sessions as eReferral participants. It is possible that cancer survivors who self-refer to exercise programs may have greater motivation to engage in programs. eReferred participants may need additional screening to determine level of readiness for exercise, and/or additional behavioral support to optimize program engagement/adherence. This finding is supported by self-referred participants' reasons for joining being more aligned with intrinsic motivation [10]. Previous studies have revealed several factors that may contribute to exercise program adherence/engagement among cancer survivors, such as demographics, medical and health status [3-11]. However, by matching participant characteristics, these findings are novel by attempting to elucidate the unique contribution of referral source on exercise program engagement/adherence. Prior studies in tobacco cessation have found that provider referred patients tend to be more racially or ethnically diverse, of lower socioeconomic status, have greater comorbidities, and lower motivation to cease the behavior when compared to self-referred patients [7-12]. If future studies determine these findings hold true for cancer survivors referred to exercise programs by oncology providers, this may present an opportunity to increase the reach of exercise programs to underserved groups. It may also address health disparities by ensuring additional resources are available to provider-referred participants to maximize program engagement.

Conclusion

Cancer survivors who are referred to a videoconference exercise program by oncology providers may not have the same level of engagement with the program as those who self-refer. Future studies are needed to determine additional strategies to engage patients eReferred by providers to promote a cancer-specific exercise program to improve health outcomes.

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