The impact of the Luton social prescribing programme on mental wellbeing: A quantitative before-and-after study

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Abstract

Background:

Social prescribing programmes expand the range of options available to primary care health professionals to address patients' psychosocial needs, impacting on their health and wellbeing. The objective of this study was to assess the change in the mental wellbeing of service users after participation in the Luton social prescribing programme.

Methods:

Skew-Normal regression was applied to analyse the change in mental wellbeing post-intervention (N=63). The short Warwick-Edinburgh Mental Wellbeing Scale (SWEMWBS) was used as the outcome measure.

Results:

The Skew-Normal regression found a statistically significant change ($p<0.0001$) in the average difference score between baseline and post-intervention measures. However, the observed change does not appear to be of clinical relevance. No significant associations in mental wellbeing scores by gender, age, or working status were found.

Conclusion:

Findings of this study indicate that social prescribing may have the potential to improve the mental wellbeing of service users. The study findings contribute to the sparse evidence base on social prescribing outcomes by socio-demographic characteristics of participants and highlight the importance of considering subgroup analysis in future research.

Introduction

Health and wellbeing is determined by a complex interaction among genetics, biological, lifestyle, psychological, social, and environmental factors [1,2]. Therefore, patients present medical and psychosocial problems, such as social isolation, debt, and housing issues, to general practitioners (GPs), who are the first point of contact to seek treatment and referrals in the English National Health Service (NHS) and other health systems globally [3–6]. However, previous research found that GPs often feel unable to manage the complex psychosocial needs of patients because of time constraints, a high workload, and little up-to-date knowledge of local non-medical services [7–11]. Although third sector organisations can provide an important source of support to address the psychosocial problems of patients [12], their support remains underused due to missing links between the health and social sectors. Thus, the traditional boundaries between hospitals, health care, and third sector organisations need to be dissolved to provide personalised and coordinated health services around the needs of the patients [13]. Partnerships between the health sector and third sector organisations are important, as the NHS does not have the resources to respond to non-medical problems such as social isolation and housing issues alone [13–15]. In response to the need of a more integrated delivery system, there have been several attempts to introduce the integration of healthcare and non-clinical sources of support in the UK [16–19]. Social prescribing is an example of a model increasingly implemented in the UK to bridge the gap between primary care and non-clinical sources of support in the community to promote self-management, health behaviour improvements, and more effective responses to psychosocial problems in primary care [10,12,20,21].

In England, social prescribing turned into a policy priority, with the aim to become an integral part of the core general practice model throughout England [22]. To refer more than 900,000 people to social prescribing schemes by 2023/24, NHS England aims to have more than 1,000 trained link workers in place by the end of 2020/21 [23]. To deliver this plan, the NHS is making its full financial contribution by reimbursing 100% of the social prescribing link workers in the future [22]. Despite the aim to establish social prescribing nationwide, the available evidence base for social prescribing programmes is weak and its effectiveness, especially in the long-term, is still to be determined [12,19,24]. The reasons for this evidence gap are manifold and may link to the diverse and interrelated outcomes of social prescribing that may be challenging to measure with quantitative pre-defined outcome measures [12]. In addition, social prescribing services were often delivered as small short-term pilots, with limited resources for evaluation [19,25].

This study focuses on a social prescribing pilot programme that was implemented in 2015 in the East of England, in Luton. The three-year pilot programme was implemented across four general practices and funded through the NHS Better Together Care Fund, which sought to integrate health and social care services in England. The Luton pathway started with a referral from a GP to a link worker. Based on the needs of the local community, the key target groups of the Luton social prescribing programme included people (18+ years old) with high risk for or diagnosis with type 2 diabetes and chronic obstructive pulmonary disease (COPD), people with mild to moderate mental health issues, people who are experiencing loneliness and/or social isolation, and carers. Following a referral, link workers then contacted referred patients to arrange an initial appointment held in surgeries. The role of link workers involved an individual assessment to identify the non-medical needs of service users, motivational interviewing, continuous personalised support, and to link service users with non-medical sources of support, to help improve their health and wellbeing. The number of sessions with link workers and intensity of provided support was dependent on the individual's needs. In the Luton scheme, link workers could refer patients onwards to twelve free sessions, usually provided by third sector organisations. Examples of such services include advice services and physical, social, and creative activities. Figure 1 summarises the pathway of the Luton social prescribing scheme.

Figure 1. Luton social prescribing scheme

The objective of this study was to assess the change in mental wellbeing of service users after participation in a social prescribing programme. In addition, this study aims to evaluate the effects of covariates (age, gender, working status) on mental wellbeing after engaging in the social prescribing service. Covariates help us describe the potential differences in proclivity, among clusters of individuals, to be affected by the intervention. Since we cannot assume a priori that all individuals will be equally affected by the intervention, we introduce covariates to explain any potential differences in wellbeing changes among individuals. This is relevant because of the wide spectrum of individuals eligible and referred to social prescribing services in Luton. Despite the importance of the inclusion of covariates in outcome analyses, it is uncommon in the available literature on social prescribing.

Methods

Setting and service

This study was set in Luton, which is a city of around 200,000 people with a large minority ethnic population. Luton is ranked as the 59th most deprived local authority in England by the

Index of Multiple Deprivation, ranging from 1 (most deprived area) to 326 (least deprived area in England) [26,27].

Design

The quantitative study to assess the mental wellbeing of patients was based on a repeated-measures design. Participants were measured before the intervention (baseline) and after the intervention (follow-up).

Data sources

Data were collected for all primary care patients referred to the Luton social prescribing programme between January 2016 and February 2018. Four link workers routinely collected data for referred patients in the first appointment (baseline) and last appointment (immediately post-intervention). The routinely collected anonymous data were used for the analysis. Written consent for the use of the anonymised data was taken from each participant of the Luton Social Prescribing programme at the point of referral to the programme.

Ethics approval

This research has been reviewed and given favourable opinion by the Institute for Health Research Ethics Committee at the University of Bedfordshire on the 16th of November 2016.

Measure of mental wellbeing: Warwick-Edinburgh Mental Wellbeing Scale (WEMWBS)

A (7-item) short English version of the WEMWBS (SWEMWBS) was developed in 2009 [28], which has been used in this study.. Answers to each item are provided using a five-point Likert scale, giving a minimum score of seven (lowest possible mental wellbeing) and maximum score of 35 (highest possible mental wellbeing) [28,29].

Covariates

The following three covariates were included in the analysis: gender, age, and working status. Initially it was planned to include more covariates in the analysis, including ethnicity, reason for referral, and type of attended services. However, the delays in developing a shared information technology (IT) system resulted in the collection of incomplete and non-standardized data for these variables, resulting in their exclusion of the analysis.

Analysis

Descriptive analysis

All included variables were analysed and visually displayed to identify outliers and examine the distribution of variables. In addition, the outcome variable was tested for normality graphically and numerically to inform further analysis [30].

Skew-Normal regression approach

Given that the commonly used paired t-test and Wilcoxon signed rank test are not appropriate, due to assumption violations (see Appendix), to assess the change in the SWEMWBS score between pre and post measures for this study sample, a regression approach using a Skew-Normal (SN) distribution was applied to analyse the asymmetric data. This approach has been proposed in modelling psychiatric measures when departures from normality occur [31]. The SN distribution is an extension of the Normal distribution for skewed data, which allows for model building, estimation, and hypothesis testing [32], through the introduction of an additional parameter α that controls the skewness [31]. The proposed SN regression (full) model is presented in the Appendix.

Model/variable selection

Backward elimination variable selection [33] based on Akaike Information Criterion (AIC) [34] was used to determine the set of significant covariates in the final model (in addition to the intercept). Forward selection [33] was also used to confirm the resulting model.

Results

Descriptive findings

In total, 448 patients were referred to the social prescribing programme and included in the database from January 2016 to February 2018. Socio-demographic characteristics (gender, age, and working status) of the 448 patients referred to the social prescribing programme and the related proportions of missing data are displayed in Table 1.

Table 1. Socio-demographic characteristics of referred patients (N=448) and proportions of missing data

Characteristics	**N (%)**
Sex	
Female	292 (65.2)
Male	144 (32.1)
Data missing	12 (2.7)

Employment	
Working	54 (12.0)
Not working	266 (59.4)
Data missing	128 (28.6)
	Mean (SD), missing data N (%)
Age	50.3 (16.8), 14 (3.1)

Of these 448 patients, 162 individuals (36.2%) completed the baseline assessment with the SWEMWBS and 68 (42% of those at baseline) completed the follow-up immediately post-intervention. Thus, the majority of participants (84.8%) were lost to follow-up or did not engage with the social prescribing service after the initial assessment and hence did not complete post-measures. Table 2 demonstrates the baseline and post-intervention mean SWEMWBS score by socio-demographic characteristics for the complete-case sample (n=63).

Table 2: Baseline and post-intervention mean SWEMWBS scores by sex, working status, and age (10-year intervals) (n=63)

Variables	**Sample size (n)**	**Baseline SWEMWBS mean (SD)**	**Post-intervention SWEMWBS mean (SD)**	**Mean difference in SWEMWBS score (SD)**
Sex				
Male	23	19.43 (6.27)	22.87 (5.00)	3.43 (4.62)
Female	40	19.90 (4.74)	22.28 (5.65)	2.38 (4.34)
Employment status				
Working	22	20.86 (6.35)	22.64 (6.01)	1.77 (4.69)
Not working	41	19.12 (4.62)	22.41 (5.10)	3.29 (4.26)
Age (10-year intervals)				
24-33	11	18.64 (3.67)	20.18 (4.67)	1.55 (3.64)
34-43	11	18.91 (6.11)	19.82 (5.23)	0.91 (3.05)
44-53	16	18.13 (6.43)	22.19 (4.64)	4.06 (5.66)
54-63	13	22.77 (4.62)	25.00 (5.37)	2.23 (3.06)

64-73	8	20.38 (3.38)	26.38 (5.04)	6.00 (5.58)
74-83	4	20.25 (5.62)	21.50 (6.24)	1.25 (1.50)

The descriptive analysis indicates that there were observed differences between the mean changes in the SWEMWBS score between gender, working status, and age. In general, there was an observed increase in mental wellbeing across gender, working status, and age, however, the magnitudes of change differed. The average increase in SWEMWBS scores was almost twice as much for participants classified as not working (mean difference=3.29) compared to those classified as working (mean difference=1.77). In addition, the observed difference in mean changes in the SWEMWBS score for males (mean difference=3.43) was also higher than that for females (mean difference=2.38). Another large divergence in SWEMWBS mean score changes was observed between the age group 34-43 years (mean difference=0.91) and 64-73 years (mean difference=6). The association of these covariates with the difference in SWEMWBS score is described in the following section.

SN regression and variable selection

Both AIC-based variable selection methods resulted in the intercept-only model as that which best explains the differences in scores. All the covariates explored, namely sex (p=0.150), age (p=0.171), and employment status (p=0.288), were non-significant in the final model. The parameter details for this final model are included in Table 3.

Statistical relevance

Results of the SN regression in Table 3 show a statistically significant change (p<0.0001) in the average difference score between baseline and post-intervention measures. The SWEMWBS score increased from baseline to post-intervention measures by an average of 2.78 points (95% CI 1.68, 3.88) within the sample, providing statistically significant evidence of an improvement in SWEMWBS score as a result of the intervention.

Table 3. Intercept-only SN regression results following model selection (n=63)

Variable	**Regression coefficient**	**Standard error**	**p-value (95% CI)**
Intercept (β_0)	2.78	0.55	p<0.0001 (1.68,3.88)

However, the mean difference in scores is smaller than the minimal clinically significant difference of three points [35,36].

Discussion

Main finding of this study

The results of the SN regression show a statistically significant change ($p<0.0001$) in the average difference score between baseline and post-intervention wellbeing measures. The SWEMWBS score increased from baseline to post-intervention by an average of 2.78 points (95% CI 1.68, 3.88). However, the mean increase identified in this study is slightly below the three points difference considered as clinically significant [35,36]. Based on this result, we cannot conclude that the mean difference in SWEMWBS scores is clinically relevant.

A high loss of follow-up is a challenge commonly cited in the social prescribing literature [24]. The link worker turn-over and consequently fragmented service delivery in the Luton programme may have had a negative impact on service user adherence, and therefore may partly explain the high loss of follow-up. Another possible reason may be experienced barriers to access the prescribed services, resulting in a drop-out of the programme. However, it remains unclear why only 162 individuals (36.2%) out of the 448 referred patients completed the baseline assessment with the SWEMWBS in the Luton programme. Link workers reported the following common barriers for service users to the completion of the baseline assessment: language barriers; difficulties to understand the wording of the SWEMWBS questions; not feeling in the right mental state to participate in the assessment; and failure to develop a shared information IT system to support complete and standardized data collection. However, the authors suggest that more qualitative research is needed in this field to gain a comprehensive understanding of the observed trends.

What is already known on this topic

Contrary to the results from our study, the study by Wiegfield et al. [37] found no statistically significant difference in mental wellbeing, measured with the SWEMWBS, post-intervention. However, consistent with the results of our study, other research identified a statistically significant improvement in mental wellbeing measured with the WEMWBS from baseline to post-intervention [25,38]. These previous studies used paired t-tests to assess the change in WEMWBS scores post social prescribing (i.e., uncontrolled before-after-study design) [25,38]. However, it is unclear whether the data was checked against, and met, the assumptions of the paired t-test in previous studies examining the impact of social prescribing on mental wellbeing.

What this study adds

Two prior studies have explored the associations of covariates in the quantitative outcome analyses of social prescribing programmes in the UK [25,28]. Consistent with our results, Woodall et al. [25] found no significant association in mental wellbeing scores by gender or age, and Ng Fat et al. [28] found no significant difference by age. Our research is unique in providing insight into the mental wellbeing outcomes of social prescribing by working status, as well as being one of only a few studies that assess the association by gender and age. Furthermore, unlike one of these previous studies that used paired t-tests, which is unclear whether the tests aligned with distributional assumptions, and did not appear to adjust for multiple comparisons [25], our analysis is uniquely based on the skew normal regression model which is more aligned with the nature of the data. Thus, a key strength of our study is the proposed flexible model approach to overcome some of the non-standard features in the data, such as its strong skewness. Successful interventions will not necessarily preserve the distributional properties of the underlying outcomes, as individuals are expected to show different levels of increase in wellbeing in addition to the expected noise when measuring outcome variables at two time points (pre and post-intervention). This translates into the potential for large skewness when measuring differences in outcomes, and, therefore, implies a departure from traditional distributional assumptions and associated tools for analysis. Although more research in this field is required to develop a deeper understanding of the outcomes of social prescribing by different groups, these results contribute to the sparse evidence base on social prescribing outcomes by socio-demographic characteristics of participants and highlight the importance of considering subgroup analysis in future research.

It is important to note that the outcomes of complex interventions, such as social prescribing, can be influenced by the implementation process, contextual factors, and delivery models [39,40]. Therefore, results of this study may not be generalisable across settings, populations, and other social prescribing programmes. Nevertheless, results of this study can provide important information and guidance for policy makers, commissioners, and providers planning to implement, or up-scale, integrated care programmes within primary care in the UK and beyond. Considering that psychosocial problems and an increasing prevalence of (multiple) chronic conditions are global challenges, social prescribing is an internationally relevant concept. Although the term 'social prescribing' is mainly used in the UK, similar community referral schemes exist across Europe, Australia, New Zealand, Taiwan, Canada, and the U.S. [41]. Based on results from such types of programmes in these additional locations worldwide, including multiple randomized controlled trials, there are many implications of social prescribing programmes for health policy and practice. These include greater cost-effectiveness, fewer doctor visits, decreased medication use, lower levels of social isolation, and higher levels of community involvement compared to current practices

and/or standards of care [41]. This study contributes to the still scarce literature on social prescribing programmes and can serve to inform policy-makers on alternative tools for health promotion, primary prevention, early detection, and management of chronic conditions. The conclusions herein provide further evidence of the overall effectiveness of such programmes as useful tools for improving health outcomes, particularly in under-served populations.

Limitations of this study

This study has important limitations to consider. Similar to most evaluations of social prescribing programmes in the UK, this study is limited by missing data, high loss of follow-up, and a short-follow up period (i.e., immediately post-intervention) [24,25]. Another limitation of this before-and-after study is the lack of a control group. It was not possible to compare outcomes from those engaging with the service with those who did not, due to practical and resource issues. Thus, the results of this before-and-after study need to be interpreted with caution, as it is possible that the observed differences are attributed to other factors, rather than the engagement in the Luton social prescribing service. In order to strengthen the evidence base on social prescribing and overcome these common methodological limitations in future studies, the development of evaluation frameworks at an early planning stage, sufficient resources, and the supporting technological infrastructure to evaluate integrated care services are required.

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Conflict of interest

The authors declare that they have no conflict of interest.

Appendix

Traditional estimation approaches

The difference score is defined as the score post-intervention minus the score pre-intervention for each individual in the sample. The alternative hypothesis (H_1) of interest is whether the mean difference (μ_D) for the general population is nonzero as a result of the intervention [42], in other words:

H_0: $\mu_D = 0$

H_1: $\mu_D \neq 0$.

The paired t-test requires normality of the differences in scores, for which the data are tested [30,43]. However, data collected in this study did not validate the normality assumption (Shapiro-Wilk p=0.018), and therefore the use of a paired t-test would have resulted in unreliable results [44]. Thus, besides its frequent use, the paired t-test may not be an appropriate method to assess the difference between SWEMWBS mean scores pre- and post-intervention. When the normality assumption is violated, the Wilcoxon signed rank test, which is the non-parametric counter part of the paired t-test and does not require normality, is oftentimes used as an alternative [30,45]. However, the Wilcoxon signed rank test is most powerful for a symmetric distribution of the population differences, an assumption for which we have no basis, especially as the sample shows strong signs of asymmetry, making this test also potentially inappropriate for this study [30].

Skew-Normal regression approach

The proposed SN regression (full) model can be represented as follows:

$D_i = \beta_0 + \beta_1 X_i + \varepsilon_i$ where $\varepsilon_i \sim$ i.i.d. $SN(0, \sigma, \alpha)$

where D_i represents the difference in scores (post SWEMWBS - pre SWEMWBS) for the i^{th} individual ($i = 1,\ldots,n=63$ in this study), with intercept β_0; ε_i represents zero-mean, independent and identically skew-normally distributed errors with common standard deviation, σ, and skewness, α; and X_i denotes any set of covariates that could potentially (linearly) explain additional variability in the difference score through a linear exposures vector β_1. Note that if $\beta_1=0$, there could still be differences due to the intervention if $\beta_0 \neq 0$ (in this case not explained/enhanced by any covariate).

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