Maximizing the public health impact of eating disorder services: A simulation study

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Abstract

Objective: Although effective interventions for eating disorders (ED) are available, the impact of health care services on a population level is far from satisfactory. A mathematical model of how health care for ED affects the population’s disease burden can stimulate discussions and provide guidance about promising strategies to reduce ED-related suffering on the population level.

Methods: The current health care situation for ED is modeled taking into account the reach and effectiveness of prevention, treatment, and aftercare, as well as incidence rates, relapse rates, and rates for spontaneous remissions. A first-order Markov model is applied and the effect of changes in single service parameters on the populations overall disease burden are simulated.

Results: Improvements of treatment utilization and the reach of prevention programs would have the largest effects on the population’s disease burden. Improving the efficacy of treatment, prevention, and aftercare show only limited effects.

Discussion: In order to maximize the public health impact of health care for ED new models of treatment delivery as well as public health approaches to the prevention of ED are critical.

KEYWORDS
burden of suffering, eating disorders, public health, service research, simulation

1 | INTRODUCTION

Effective evidence-based interventions for prevention (Stice & Shaw, 2004; Stice, Shaw, & Marti, 2007; Heinicke, Paxton, McLean, & Wertheim, 2007; Taylor et al., 2006), treatment (Brownley, Berkman, Sedway, Lohr, & Bulik, 2007; Bulik, Berkman, Brownley, Sedway, & Lohr, 2007; Hay, Bacaltchuk, Stefano, & Kashyap, 2009; Shapiro et al., 2007), and relapse prevention (Bauer, Okon, Meermann, & Kordy, 2012; Fichter et al., 2012) for eating disorders (ED) are available. Unfortunately, only a minority of people suffering from an ED seek treatment (Hart, Granillo, Jorm, & Paxton, 2011), and specific relapse prevention interventions are not part of routine care. Health promotion and prevention programs are not area-wide implemented, and engaging people in ED prevention is challenging (Atkinson & Wade, 2013; Moessner, Minarik, Ozer, & Bauer, 2016). In addition, the transfer from research to practice is ineffective, interventions that have demonstrated their efficacy in trials are not being broadly implemented into routine care. Furthermore, not all sufferers that seek help receive evidence-based treatment (Cooper & Bailey-Streubel, 2015; Fairburn & Wilson, 2013; Hart et al., 2011; Kazdin, 2008; von Ranson, Wallace, & Stevenson, 2013; Waller, 2016). As a consequence of these factors, the overall impact of ED services on the population’s disease burden is limited, and the overall public health impact of health care is relatively low (Kazdin, Fitzsimmons-Craft, & Wilfley, 2017).

The public health impact of an intervention can be defined as the product of its effectiveness and its reach (Glasgow, Lichtenstein, & Marcus, 2003). Effectiveness in that context depends on both the intervention’s efficacy and the quality of its dissemination, that is, its fidelity in routine care (Wallace, Blasé, Fixsen, & Naoom, 2008).

As the definition of impact is multiplicative in nature, if one of the multiplier equals zero, the public health impact equals zero as well. Furthermore, when impact is defined as the product of its effectiveness and its reach, it is possible that the intervention’s efficacy and the quality of its dissemination, that is, its fidelity in routine care (Wallace, Blasé, Fixsen, & Naoom, 2008).

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intervention that reaches a larger proportion of the target population, can be equal or even superior in terms of its public health impact. For example, an intervention that is effective for only 30%, but utilized by 70% of the target population has a larger public health impact than an intervention that is effective for 80%, but only utilized by 20% (0.30 × 0.70 = 0.21 vs. 0.80 × 0.20 = 0.16).

Yet, the situation is more complex, as the potential impact of introducing an intervention into the routine does not only depend on its effectiveness and reach, but in addition on the performance of other service sectors. For example, the public health impact of treatment is influenced by the effectiveness and reach of prevention, and the effectiveness and reach of aftercare interventions. In other words, the majority of effects on the overall public health impact are interactional effects, that is, the effects of changes of a parameter depend in most cases on the current status of at least one other parameter (e.g., the more patients utilize a treatment (reach) the higher the public health impact of improving the efficacy of that treatment).

Because of these complex interdependencies the broader picture of how changes in health care affect the ED related disease burden on a population level is often neglected.

Mathematical modeling can “help guide the field in where to place the emphasis not only in delivering but also in developing interventions” (Kazdin & Blase, 2011; p. 31). A model can help to better understand the topic under investigation and allows to make estimations and predictions of the effects that changes in health care services would cause. By comparing the consequences of alternative scenarios (=parameter settings), a model can be employed to estimate the effects of actions and describe the potential of alternative future directions. Thus, it can stimulate discussion in a field and guide decision-making processes.

This study models the relations between mental health services for ED and the population’s disease burden. By exploring the effects of alternative parameter settings (i.e., changes in health care), potentials of different strategies to maximize the public health impact of services will be quantified, and most promising starting points will be identified.

2 METHODS

A simulation study was conducted in order to explore the effects of changes in health care on the population’s overall disease burden. The first-order Markov model contains effects and reaches of health care interventions1 and takes into account incidence rates, relapse rates, and spontaneous remission rates in order to estimate yearly transition probabilities between healthy and diseased.

2.1 Model parameters

Following a review of the relevant literature, articles were included that report rates and percentages (as opposed to scale means) for the model parameters. Both randomized controlled trials and observational studies were taken into account in order to estimate the model parameters.

Table 1 displays the model parameters, on which the simulations are based.

As model parameters represent yearly transition rates between healthy and diseased, studies reporting effects on ED symptoms or scales were neglected. In addition, as the model does not differentiate between different types of ED, estimates were interpolated between different EDs and in case of time periods that were shorter or longer than one year. The estimated prevalence rates are combined prevalence rates that do not differentiate between different eating disorders.

2.2 Definition of disease burden

Based on the model parameters yearly transition probabilities between healthy and diseased were calculated.

Transition from healthy to diseased:

\[
\text{inc} \times (1 - \text{preven}) \times r_{\text{preven}}
\]

(1)

Transition from diseased to healthy:

\[
\text{effect} \times \text{eff} \times \text{util} + \text{rem} \times (1 - \text{eff} \times \text{effect} \times \text{util} + \text{eff} \\
\times \text{effect} \times \text{util} \times (\text{relapse} - \text{relapse} \times \text{after} \times r_{\text{after}}))
\]

(2)

Assuming validity of the Markov assumptions, these transition probabilities are sufficient to calculate the resulting population’s prevalence rate, that is, the disease burden.

2.3 Simulations

Alternative parameter settings are simulated for the parameters of interest (Table 1) and the resulting population’s disease burden is reported. Without any health care the model’s prevalence rate is 6.98%, which serves as reference value for the simulations representing 100% disease burden. Results will be reported relative to this value.

2.4 Sensitivity analyses

In order to take into account the insecurity of the estimates and to explore the stability of the conclusions of the model parameters, sensitivity analyses are conducted. For that purpose, all parameters are drawn from a normal distribution (truncated at 0 and 1), which standard deviations represent insecurity (see SD column in Table 1). This procedure was repeated 5,000 times and the cumulative density functions of the resulting disease burden reductions for 10 and 20% improvements for each of the seven parameters are provided. All analyses were performed using Matlab.

3 RESULTS

Figure 1 displays the results of the simulations. The vertical axis represents the population’s prevalence (i.e., the disease burden, relative to the prevalence without health care), the horizontal axis represents

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1Although in some settings prevention is not considered an aspect of health care.
changes of the model parameters assuming that the others are constant.

The prevalence rate for the estimated effects is 5.73%. The model’s prevalence is in line with epidemiological data for young females (Hoek, 2016; Keski-Rahkonen & Mustelin, 2016), supporting the validity of the model. This rate equals a reduction of 17.85% (lower horizontal line in Figure 1). This reduction can mainly be attributed to the effects of treatment. Removal of treatment would result in a disease burden of 96.27% (3.73% reduction [top horizontal line in Figure 1]), which could be attributed to prevention. Removal of prevention would result in a disease burden of 85.37% (14.63% reduction [second horizontal line in Figure 1]), caused by treatment and aftercare.

The reach of prevention and the reach of treatment show the steepest trajectories, that is, having greater proportions of the population engage in prevention programs or seek treatment would have the largest effects on the population’s prevalence rate. An increase of 10%

### TABLE 1  Model parameters

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Definition</th>
<th>Estimate</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>inc</td>
<td>Transition rate from healthy to diseased in one year</td>
<td>.015</td>
<td>.004</td>
</tr>
<tr>
<td>rem</td>
<td>Transition rate from diseased to healthy in one year</td>
<td>.2</td>
<td>.05</td>
</tr>
<tr>
<td>preven</td>
<td>Proportion of transitions from healthy to diseased prevented</td>
<td>.4</td>
<td>.2</td>
</tr>
<tr>
<td>r_preven</td>
<td>Proportion of target population participating in a prevention program</td>
<td>.1</td>
<td>.05</td>
</tr>
<tr>
<td>effect</td>
<td>Proportion of successful treatments that result in a transition from diseased to healthy</td>
<td>.55</td>
<td>.05</td>
</tr>
<tr>
<td>util</td>
<td>Proportion of diseased seeking treatment</td>
<td>.23</td>
<td>.04</td>
</tr>
<tr>
<td>eff</td>
<td>Proportion of successful treatments in routine care compared to treatment effect (see above)</td>
<td>.7</td>
<td>.2</td>
</tr>
<tr>
<td>relapse</td>
<td>Proportion of successfully treated patients, that relapse</td>
<td>.5</td>
<td>.1</td>
</tr>
<tr>
<td>after</td>
<td>Proportion of relapses prevented by participation in an aftercare program</td>
<td>.4</td>
<td>.1</td>
</tr>
<tr>
<td>r_after</td>
<td>Proportion of successfully treated patients that participate in an aftercare/maintenance program</td>
<td>.1</td>
<td>.05</td>
</tr>
</tbody>
</table>

Note. * aSD = standard deviation used in the sensitivity analysis; b Taken from Grilo et al. (2003), Milos, Spindler, Schnyder, and Fairburn, (2005), Fairburn, Cooper, Doll, Norman, and O’Connor (2000); c Taken from Taylor et al. (2006); Stice et al. (2008); d Taken from Hay et al. (2009), Fairburn et al. (1995); e Taken from Hart et al. (2011); f Taken from Lowe, Bunnell, Neeren, Chemyak, and Greberman, (2011); Richard (2005); g Taken from Bauer et al. (2012), Keel and Mitchell (1997); h Taken from Bauer et al. (2012).

### FIGURE 1  The population’s disease burden as a consequence of changes in health care as predicted by the model. Note. Horizontal lines: (a) Prevention only: treatment efficacy assumed to be 0; (b) Treatment and aftercare only: prevention efficacy assumed to be 0; (c) currently: parameters from Table 1 [Color figure can be viewed at wileyonlinelibrary.com]
(20%) in treatment utilization would decrease the number of cases by an additional 4.92% (9.29%), an increase of 30% (50%) would cause a decrease in the disease burden by 13.19% (19.85%). Disseminating prevention programs to an additional 10% (20%) of the population would result in a decrease of the population’s disease burden by 3.17% (6.48%), distributing it to 30% (50%) would cause a decrease of 9.75% (16.33%). An improvement in treatment efficacy of 10% (20%) would reduce the disease burden by 2.13% (4.51%; see Figure 1). Increasing treatment efficacy to 100% (i.e., assuming that every treatment is successful) would yield a reduction of 8.8%.

The effects and reach of aftercare show the flattest trajectories. They do not have a main effect in the model and thus depend on the factors they interact with [see eq. (2)].

3.1 | Sensitivity analyses

Figure 2 displays the results of the sensitivity analyses. For each of the seven parameters it shows the cumulative density functions for 10 and 20% improvements taking into account insecurity of the parameter estimates. The horizontal axis represents additional reductions in the population’s disease burden.

Although the estimations for improvements vary substantially, the core findings are stable (the curves are parallel): an increase of treatment utilization and an enhanced reach of prevention efforts have the largest effects on the population’s disease burden.

4 | DISCUSSION

The model illustrates the current situation of health care services for EDs and offers valuable insights into the interplay of health care sectors. It allows to numerically estimate the consequences of changes to current health care and thus can support decision-making processes.

According to the model, current health care services for ED reduce the population’s overall disease burden by only 17.85%. This effect can mainly be attributed to the effects of treatment and to a minor degree to prevention. This situation is far from satisfactory. Despite the achievements in research and practice over the last decades, the majority of sufferers does not utilize and therefore not benefit from health care, yet. The most promising strategies to improve the current situation are to maximize treatment utilization and to engage more people in prevention programs. Expanding the reach of ED treatment and prevention have shown the steepest trajectories for every percent of improvement. They show the greatest potential with respect to the maximum reduction of disease burden. In addition, these areas seem to be promising targets as there is still lots of room for improvement: only a minority of sufferers seeks treatment for their ED (Hart et al., 2011). Despite the importance of prevention, its reach is still small. As long as the reach of treatment is not increasing, improving the efficacy of treatment has only limited potential.

Figure 1 just displays results for changes in single parameters, assuming that the others remain stable. As all effects are interactional, the effects of improvements of a single parameter always depend on the current status of other parameters. This is especially obvious for the estimated potential of relapse prevention programs.

For example, the assumed reach (.23), effect (.55), and effectiveness (.7) of treatment reduce the effects of changes in aftercare efficacy and its reach by 91.15% (100% × [1 - .23 × .55 × .7]). The same principle applies to the other parameters. In that sense, the results are only a snap-shot of the current situation.

Yet, knowing the most promising starting points is not sufficient, innovative strategies to improve the public health impact of ED services are needed. As the barriers to seek treatment are multifaceted (Ali et al., 2016), the solutions need to be multifaceted, as well (Kazdin et al., 2017). Innovative ways of treatment delivery, that extend the reach of specialized centers, seem to be one promising mean. As an example, therapy can be delivered via technology, so that sufferers who are not able to utilize face-to-face treatment (e.g., long distances to treatment centers, limited mobility, unstable living situation due to work-related travels, etc.) are provided with other options (Mitchell et al., 2008; Zerwas et al., 2017). In addition to new ways of treatment
delivery, low intensity, easy access, anonymous interventions trying to maximize reach rather than efficacy are a valuable addition to current services (Kazdin & Blase, 2011; Wilson & Zandberg, 2012). They may also reduce the barriers like stigmatization and shame and facilitate treatment uptake (Moessner et al., 2016). Another strategy to facilitate help-seeking and treatment utilization are population-based health programs that aim at promoting awareness, reducing stigma, increasing mental health literacy (Mond, 2014). Furthermore, targeting larger societal conditions rather than focusing on individuals might be a promising approach to increase the public health impact (Austin, 2016; Rodgers, Ziff, Lowy, Yu, & Austin, 2017).

The fact that most of the effects are interactional, highlights the need to overcome the artificial separation of different health care sectors. This is increasingly recognized by policy makers and expressed as key component of a future health care system (eHealth Taskforce, 2012). Interventions from different sectors need to be crosslinked. For example, having the provider of the initial treatment also offer the aftercare intervention may facilitate seamless service provision, and support patients during the critical phase after treatment termination (Bauer et al., 2012; Fichter et al., 2012; Gulec et al., 2014). Another example are Internet-based programs aiming at education, prevention, early intervention, and finally referral to ED treatment, depending on the individual needs of participants (Bauer, Moessner, Wolf, Haug, & Kordy, 2009, Bauer et al. 2013; Wilfley, Agras, & Taylor, 2013).

Finally, research needs to emphasize population effects and public health impact (Austin, 2016). Criteria beyond efficacy like accessibility, compliance, reach, effectiveness, and cost allow to better judge an intervention’s potential public health impact (Insel, 2009). In addition, the success of transferring an intervention from research into practice depends on their real world usability. Not all interventions require the same degree of fidelity in order to be effective. In order to maximize the public health impact of an intervention, it would be beneficial if the translation into clinical practice did not require extensive, costly training, and if the intervention was still effective even when delivered with low fidelity. Real world usability has implications for both the potential reach on an intervention and for its effectiveness in clinical practice. It is crucial for an intervention’s potential public health impact and needs consideration when developing and testing new treatments.

The model presented in this paper is parsimonious. The parallel curves in the sensitivity analyses document the stability of the conclusions. Nevertheless, the results should be interpreted in light of the model’s shortcomings.

Although ED diagnoses are heterogeneous not only with respect to symptomatology, but also with respect to incidence, prevalence, mortality, and prognosis, the model does not differentiate between disorders. For some of the model’s parameters (reach of prevention and aftercare, effectiveness) there are hardly any reliable data available. Yet, the structure of the model needs to represent the system under investigation, and should not be determined by the availability of data (Caro, Briggs, Siebert, & Kunzt, 2012). Whether factors like health promotion or e-health might be reasonable extensions to the model is arguable.

The model does not take the long-term course of ED into consideration. In addition, chronic courses violate the Markov assumption, which results in an overestimation of the public health impact of treatment. Yet, there is a lack of data on long-term courses and chronicity in ED and more studies are needed (Wonderlich et al., 2012) to develop higher order Markov models. The most problematic aspect of the model from our point of view is the definition of disease burden as a dichotomous construct (diseased vs. healthy). From a patient’s point of view disease burden is continuous, and treatments that do not yield remission might still reduce the disease burden. In addition, the dichotomous operationalization of disease burden neglects the suffering associated with sub-clinical eating disorder symptomatology (Mond, Hay, Rodgers, & Owen, 2009). Consequently, the public health impact of interventions that aim at subclinical ED symptomatology might be underestimated. The model provides insights into the potential of changes in specific health care areas. Yet, in the context of limited resources, cost-effectiveness analyses and the development and economic evaluation of innovative care models are needed to convince stakeholders and initiate changes (Kass et al., 2017; Wang, Nichols, & Austin, 2011).

However, sensitivity analyses confirmed the stability of the overall conclusions. The model aims at providing numerical estimates for changes in health care, and at stimulating the discussion on disease burden and public health. It does not aim at comparing the importance or relevance of different sectors. Improving care for individuals suffering from mental disorders is not an either-or endeavor, it has to be an as-well-as effort. There is great potential to reduce the disease burden, if we keep in mind public health impact as a guiding principle and make ourselves think and act broadly across sectors and theories.


SUPPORTING INFORMATION
Additional Supporting Information may be found online in the supporting information tab for this article.

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