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Peer Influence on Change in Employer Appraisal of Depression Care Management Products

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Abstract

Employers may purchase evidence-based depression care management products to improve work outcomes of their depressed employees. Because employers have imperfect information about mental health products, they may rely on peers to evaluate benefits and costs of the products. We examined the impact of peer influence on employer appraisal of depression care products in a randomized controlled trial of marketing intervention for a high quality depression care product. Using a general form of the autocorrelation model in social network analysis, findings showed significant peer influences on how employers changed their appraisal of a depression care product.

Introduction

As one of the most prevalent mental disorders in the U.S. workforce [1], depression has been shown to reduce employee work engagement by increasing absenteeism [2] and lowering productivity at work [2-7]. To address these problems, employers can purchase evidence-based depression products that provide the type, intensity, and duration of depression care management [8] shown to improve employee work outcomes [9-12]. Previous researchers note that employers are willing to adopt depression products if they perceive those savings from improved work performance outweigh program costs [13-21]; however, employer soften have imperfect information to quantify the benefits of a depression product for their organization [22]. In the face of this uncertainty, employers may turn to each other to evaluate a product's benefit and cost, where the role of peer influence weighs in. Peer influence in this paper can be defined as the persons' tendency to follow their peers' decision especially when there is lack of confidence in decision making due to imperfect information.

The field has struggled to understand how peer influence impacts appraisal in the context of marketing efforts, although the relationship between peer influence and medical product appraisal has been emphasized and analyzed in a variety of settings. For example, multiple analyses of data by Coleman, Katz, and Menzel [23] examining peer influence on the diffusion of a new medication produced conflicting results [24]. Two research teams found significant peer influence [25,26], while two others found no significant peer influence after incorporating time-sensitive analyses or controlling for marketing efforts, respectively [27,28]. In contrast, recent research [29] succeeded in demonstrating significant peer influence on the adoption of a new drug using models that controlled for targeted marketing efforts.

This paper takes advantage of a unique opportunity to examine the impact of peer influence on employer appraisal of depression products in the context of a Randomized Controlled Trial (RCT) [22] of a marketing intervention to encourage employers to purchase a high quality depression product. Intervention subjects participated in a presentation providing an evidence-based estimate of the economic value of a high quality depression product to their company. Control subjects participated in a presentation encouraging the use of usual care methods to improve the quality of the depression treatment their health plans provided. We expected that employers' uncertainty about the value of a new product was likely to persist after the presentation and they would turn to their peers for feedback. Considering this, we hypothesized that peer influence would have an observable impact on the change in depression product appraisal during the 12-month period after the marketing intervention.

Our study expands this line of inquiry with three objectives. First, we examine peer influence on product appraisal using a design in which subjects were randomized to marketing, thus reducing previously identified problems arising from high correlations between social network variables and marketing efforts [28]. Second, our study examines peer influence on appraisal change, beyond looking at appraisal at a single point in time. Third, our study explicitly estimates the impact of peer influence through two distinct routes-directly through peers' appraisal changes and indirectly through peers' deviations from their expected appraisal changes-in a single general model [30].

Methods

To examine social network impact on the appraisal change, we developed a model that examined how social network contact in the year following the marketing presentation predicted change in the appraised benefit-cost ratio in the year following the presentation, controlling for baseline covariates.

Participants in the Study

Detailed information on the parent study design has been previously published [22]. Randomized employers, who belonged to regional coalitions of National Business Coalition on Health [31] or other related professional associations, were eligible to participate in the study if they represented a public or private company that provides health benefits to 100 or more domestic employees and had not previously purchased depression products for their employees. Participating employers appointed one employee from their company to represent them. The representatives were mainly senior health benefits professionals, and more than 60% of these representatives reported their strong influence in benefit purchasing decisions. Participating employers within a coalition/association were randomized to the Evidence-Based (EB) or Usual-Care (UC) condition. Then, employer representatives randomized to the EB condition received a marketing presentation from a nationally recognized employer advocate encouraging companies to purchase depression products. Employer representatives randomized to the UC condition received a presentation from the same advocate encouraging them to monitor and improve quality indicators for depression. Previous research established that the UC intervention was evidenced to have little or no impact on employer purchasing of depression products [32-36]. All employer representatives completed surveys immediately before the presentation, immediately after the presentation, and 12 months later. Forty two subjects remained in the company but refused to participate in 12-month follow-up. Seventeen subjects left the company by 12-month follow-up. Four of those subjects were replaced in 12-month follow-up by coworkers. The remaining subjects provided fully or partially completed data. All subjects (including replacement subjects) were asked about their peer communication during the year following the presentation at 12-month follow-up. Replacement subject responses to this item can reasonably be expected to be as valid as original subject responses (e.g., if replacement subjects had little communication with other coalition members during the year following presentation, they could report that). Even if replacement subjects provided biased data on peer communication or depression product appraisal, it is not likely that they introduced an observable bias into the results because they represented only 2% of the sample we analyzed. The study was approved by Institutional Review Boards at Florida State University and University of South Florida.

Variables and instruments

Dependent variable – Change in benefit-cost ratio: The dependent variable is the change in the benefit-cost ratio from the pre-presentation through 12-month follow-up period. The benefit measure in the numerator is the average of four items to measure the employer representative's appraisal of the benefit to the company if the company purchases the depression product. The four items are: (a) Would you expect the product to help depressed worker meet responsibilities at work over the short term (the first 6 weeks)?; (b) Would you expect the product to help depressed worker meet responsibilities at work over the long term (the first 6 months)?; (c) Would you expect the product to help prevent friction between a depressed worker and his/her coworkers?; (d) Would you expect the product to help reduce treatment costs that contribute to increase in health premiums the next year? All of the four items were coded as: (1) no help; (2) little help; (3) moderate help; (4) considerable help; (5) great deal of help. The benefit measure in the numerator has an alpha coefficient of 0.84. The cost measure in the denominator is the response to the question, "How would you rate the financial cost of the depression product to your organization?" The response options are: (1) much worse than programs our organization has recently undertaken; (2) worse than …; (3) better than …; (4) much better than … The cost measure item was reverse coded for our computation of the benefit-cost ratio in order to increase the ease of interpretation; thus, the higher the benefit-cost ratio is, the more favorable appraisal becomes. We calculated change by subtracting baseline ratios from 12-month ratios. The possible value of the benefit-cost ratio at each time point ranges from 0.25 through 5 (the appraised benefit to the company ranges from 1 through 5 and the cost ranges from 1 through 4), with positive change scores indicating perceptions of increasing benefits in relation to cost over 12 months.

Independent variable - Peer influence: For the weighting matrices W_1 and W_2 in Model (3) in the following section, we used the matrix of the number of within-group work-related communications indicated by each employer representative between the intervention presentation and the 12-month follow-up survey. The survey question was "During the last year, how often have you discussed work-related problems with coalition/association representatives from the following organizations in your area?" The responses were: (1) not at all (recoded as 0); (2) once/year (recoded as 1); (3) 2 - 6 times/year (recoded as 2); (4) 7 - 12 times/year (recoded as 3); (5) twice a month (recoded as 4); (6) weekly (recoded as 5); and (7) more than weekly (recoded as 6). The missing values were coded as zero because if a representative does not remember any communication with someone it is highly likely that her appraisal would not be influenced by this particular person. Since the frequencies were indicated among the companies within the same coalition/association, no communications were recorded between two representatives from different coalitions/associations. Also, the matrix is not symmetric because one representative of a pair may have a different criterion in counting the number of communications from the other representative of the pair. The higher the frequencies, the more influence the subject is expected to receive from peers or provide to peers.

Covariates: The demographic variables measured in the RCT [22] were used for intrinsic attributes of employer representatives such as: (a) gender; (b) race; (c) age (measured in ten-year intervals); (d) job experience (total years in the field). Age data were collected in ten-year intervals to increase subject likelihood of responding because older representatives may be reluctant to reveal their age. Because the main focus of the study was the influence of peer communications among employer representatives, the company attributes other than representative attributes were not incorporated in the study. Since

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the data were obtained from an RCT to test the effectiveness of the treatment intervention, we included the binary variable indicating the Evidence-Based (EB) marketing intervention *vs.* Usual-Care (UC) intervention in data analyses. We also controlled for social network density to differentiate the impact of peer influence on appraisal change from overall connectedness within the network because network density may strongly affect the quality of the estimates of peer influence [37]. Identical for all subjects within the same coalition/association, social network density was measured by the number of ties present in the coalition/association divided by the total number of ties that could be present in the coalition/association [38].

Network autocorrelation models

When actors in a social network influence each other's opinions, an actor's opinions are not independent of those of the other actors in the network. Thus, a key assumption of Ordinary Least Squares (OLS) regression models, namely, independence of observations, is violated due to autocorrelation. To directly incorporate peer influence in the analysis while resolving the problem of interdependence of observations in the dependent variable, we use a form of network autocorrelation models. An additional advantage of the model is the capability of coefficient estimation for covariates as in OLS regression [39].

Using the model descriptions and notations by [30], the network effects model is expressed as

$$y = \rho Wy + X\beta + \varepsilon, \tag{1}$$

where y is a vector of values of the dependent variable, ρ measures the magnitude of the network effect, W is a weighting matrix related to the ties connecting actors in a network, X is a matrix of values of covariates, β is a vector of coefficient parameters for covariates, and ε is a vector of error terms that are normally distributed with zero means and equal variances. Wy can be interpreted as the vector of weighted averages of all y, which implies that an actor's opinion is influenced by the weighted average of the peers' opinions. In the network effects model, an actor forms her own opinion based both on her intrinsic opinion as measured by covariates and on her influential peers' opinions. Model (1) has been studied by other researchers [30,39-44].

Table 1: Profiles of employer representatives (*n*=189).

Variable	%	Mean	S.D.
Gender (female)	67.7		
Race (white)	88.4		
Age			
21 – 30 (coded as 1)	5.8		
31 – 40 (coded as 2)	20.1		
41 – 50 (coded as 3)	29.1		
51 – 60 (coded as 4)	38.1		
61 – 70 (coded as 5)	6.3		
71 – (coded as 6)	0.5		
Job experience		18.28	11.72
Network density*		0.33	0.23
EB intervention	50.3		
Change in Benefit-Cost ratio		0.08	0.66
At pre-intervention			
Benefit-Cost ratio**		1.49	0.51
Benefit**		3.91	0.75
Cost***		2.83	0.73
At 12 months			
Benefit-Cost ratio**		1.57	0.57
Benefit**		4.01	0.77
Cost***		2.77	0.77

Note: *Among 20 coalitions/associations with a positive network density **higher scores indicate greater perceived organizational benefit-cost ratios or greater organizational benefits ***lower scores indicate lower costs relative to other programs.

Model (1) captures one way that the opinions of connected actors could be correlated. Another way that correlation in the opinion of connected actors could arise is through correlated error terms when opinion is modeled as determined by actor attributes. This alternative model is the network disturbances model that [30] expressed as

$$y = X\beta + \varepsilon, \quad \varepsilon = \rho W\varepsilon + \upsilon, \tag{2}$$

where υ is a vector of independent random disturbances of ε, and ρ measures the strength of the network autocorrelation through ε. As O'Malley and Marsden [42] observe, in the network effects model, one actor's opinion has a direct effect on the opinions of other actors and this is consistent with an influence process while in the disturbances model, the interdependence of error terms could be "due to various processes, such as ecological influence or environmental molding, that do not involve direct effects of actors on one another [45]. Leenders [30] expresses the point differently – in the disturbances model, an actor's opinion is not directly influenced by her peers' opinions themselves. Rather, she observes how her influential peers deviate from their expected intrinsic opinions; then she adjusts her own deviation from her expected intrinsic opinion based on her peers' deviations. Model (2) was studied by Doreian [46], Dow, Burton, and White [47], White, Burton, and Dow [48], Leenders [30], and O'Malley and Marsden [42] among others.

The autocorrelation model used in the present study is a generalized model that combines network effects of Model (1) and network disturbances of Model (2). It is discussed in Leenders [30] and O'Malley and Marsden [42], and expressed as

$$y = \rho_1 W_1 y + X\beta + \varepsilon, \quad \varepsilon = \rho_2 W_2 \varepsilon + \upsilon \tag{3}$$

where $W_1 = W_2$ is allowed and subscripts 1 and 2 represent the weighting matrices in Models (1) and (2), respectively. We used the matrix of peer influence described in Section of *Independent Variable* for the weighting matrices W_1 and W_2. In this general model, the correlation between the opinions of adjacent actors is produced in two ways: directly through social influence that peers have on one another's viewpoints and indirectly through the error terms even once influence and actor attributes are accounted for. Although Model (3) is a very general model, it has not been fitted often like Model (1) or (2). It was studied by Doreian [49] and Rietveld & Winters oven [50], but those studies fitted the model using simulated data or in the context of spatial analysis. No previous research has estimated Model (3) using empirical data in the context of social network analysis.

Data analysis

Standard regression estimation methods cannot be used to fit the model due to autocorrelation. The research team used the lnam function from the sna package [51] in R https://www.r-project.org/ for the autocorrelation model of the present study. R is open-source free statistical computing software, and the sna package has been used for social network analysis in numerous studies [52-54]. The model required subjects to have complete data on all variables used in the analysis.

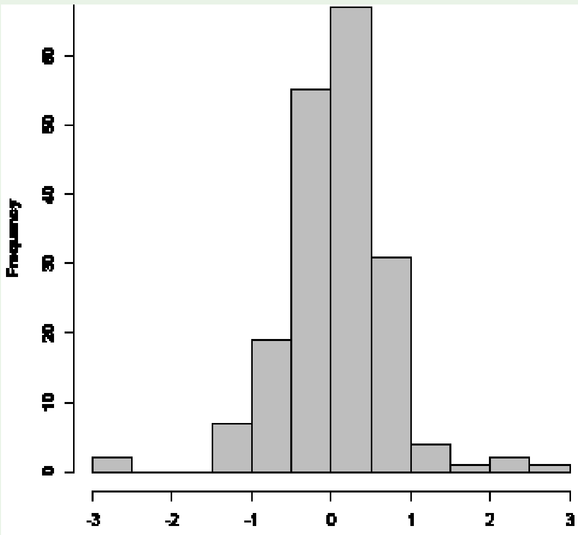

Figure 1: Histogram of the change in benefit-cost ratio (*n*=189). (Mean=0.08, SD =0.66, skewness=0.01, kurtosis=3.83).

Results

Two hundred thirty nine of 293 employer representatives (82%) in 29 coalitions/associations completed both interviews. One hundred eighty nine of 239 subjects (79%) completed data on all variables used in this analysis. The 189 subjects with complete data and the 50 subjects with incomplete data were comparable with no significant difference in all covariates (*p*-values = 0.159 – 0.911 for χ^2-tests or *t*-tests). Characteristics of these 189 subjects used in our analysis are summarized in (Table 1).

Also presented in (Table 1) are the subject's appraisals of the depression product t baseline and 12 months. The overall benefit appraisal slightly increased and the overall cost appraisal slightly decreased during the 12-month period after intervention. The average change in the benefit-cost ratio (0.08) indicates a non-statistically significant improvement (*p*-value = 0.154 for *t*-test) during the 12-month period. These findings imply that, on average, there was no overall change in all employer representatives' appraisal during this period. These findings are consistent with the fact that the marketing intervention in this RCT showed no effectiveness in appraisal change. However, we cannot conclude that individual appraisals did not change - in fact, it is quite possible that there was much individual change but in offsetting directions so that those who were initially favorable became more favorable and those who were initially unfavorable moved to an even more unfavorable appraisal thereby leaving the average appraisal unchanged. It should be noticed that the autocorrelation model does not simply analyze the average change in appraisal after intervention. Rather, the model analyzes the impact of peer influence on the appraisal change after intervention, by incorporating autocorrelation of the main outcome variable that appears on the both sides of the equations of Model (3). Table 2 displays the comparison between the EB and UC groups and there was no significant difference for all items between two groups based on χ^2-tests or *t*-tests. The average change in the benefit-cost ratio shows no significant change of appraisal for both groups (*p*-value= 0.569 and 0.136 for the EB and UC groups, respectively). Figure 1 shows that the distribution of our dependent variable is close to a normal distribution. The results from our autocorrelation model are shown in (Table 3). Peer influence appears to have significant impacts on the change in appraisal along time. All predictors except peer influence are non-significant predictors of appraisal change. In evaluating the network effects directly through appraisal change itself, the positive value (0.060) of ρ_1 indicates that appraisal change is influenced by

Table 2: Profiles of employer representatives for EB and UC groups.

	EB (*n*=95)			UC (*n*=94)			EB *vs.* UC	
Variable	%	Mean	S.D.	%	Mean	S.D.	χ^2 or *t*	*p*-value
Gender (female)	66.3			68.4			0.174	0.677
Race (white)	86.3			89.5			0.776	0.378
Age							4.383	0.496
21 – 30 (coded as 1)	8.5			3.2				
31 – 40 (coded as 2)	18.9			21.1				
41 – 50 (coded as 3)	26.6			31.9				
51 – 60 (coded as 4)	40.0			35.8				
61 – 70 (coded as 5)	5.3			7.4				
71 – (coded as 6)	1.1			0.0				
Job experience		18.72	12.36		17.83	11.08	-0.521	0.603
Change in Benefit-Cost ratio		0.05	0.70		0.11	0.63	0.680	0.498
At pre-intervention								
Benefit-Cost ratio*		1.53	0.55		1.45	0.47	-1.061	0.290
Benefit*		4.00	0.74		3.82	0.76	-1.713	0.088
Cost**		2.85	0.79		2.80	0.67	-0.518	0.605
At 12 months								
Benefit-Cost ratio*		1.57	0.59		1.56	0.56	-0.157	0.876
Benefit*		4.06	0.71		3.96	0.81	-0.862	0.390
Cost**		2.81	0.79		2.72	0.75	-0.776	0.439

Note: *higher scores indicate greater perceived organizational benefit-cost ratios or greater organizational benefits **lower scores indicate lower costs relative to other programs.

Table 3: Results for autocorrelation model (*n*=189).

Term	Estimate	S.E.	*t*-value	*p*-value
Intercept	–0.042	0.221	–0.191	0.848
Gender (female)	0.117	0.099	1.175	0.240
Race (white)	0.132	0.143	0.924	0.355
Age	0.008	0.050	0.164	0.870
Job experience	–0.005	0.005	–0.982	0.326
Network density	–0.093	0.171	–0.542	0.588
EB intervention	–0.020	0.094	–0.209	0.835
ρ_1 (directly through appraisal changes)	0.060	0.018	3.289	0.001
ρ_2 (indirectly through disturbances)	–0.091	0.036	–2.512	0.012

Note: The dependent variable is the change in the employer representative's appraisal of the benefit-cost ratio for the depression product.

peer appraisal change in the same direction. For example, if one's peers report an increase (decrease) in the appraised benefit-cost ratio, then she too will report an increase (decrease) in the appraised benefit-cost ratio. In evaluating the network effects indirectly through disturbances, the negative value (–0.091) of ρ_2 indicates that an employer representative responds in the opposite direction from her peers' deviations from their expected intrinsic opinions.

Discussion and Conclusion

Peer influence clearly played a significant role on employer appraisals of depression products over time. Using longitudinal data collected nationally from 29 employer groups in an RCT over one-year period, the current study demonstrated significant peer influences on how employers changed their appraisal of a depression product independent of the marketing they received. By taking advantage of a general form of the autocorrelation model in social network analysis, two different routes of peer influence were observed: (1) directly through peers' appraisal changes themselves in the same direction (positive ρ_1), and (2) indirectly through peers' deviations from the expected appraisal changes in the opposing direction (negative ρ_2).

The significance of ρ_1 and ρ_2 supports previous studies about social network influence on people's attitudes or behaviors [25,39,55-57]. For example, the positive value of ρ_1 supports the argument that favorable (unfavorable) opinions may grow stronger in interactions with people who have favorable (unfavorable) perceptions [39]. Importantly, we found significant evidence of peer influences after controlling for marketing intervention, which is in line with the finding by [29]. Indeed, the marketing intervention showed no significant effect on the appraisal change in our study. This result suggests that peer influence in these employer groups were so strong that they superseded the marketing intervention, in contrast to previous research in which peer influence was wiped out after controlling for marketing efforts [28]. The significant "contamination" or "spillover" effect of the social network appears to partially contribute to no appraisal change in the 12-month period.

Although ρ_2 is not as straightforward as ρ_1 in interpretation, the negative value ρ_2 in the context of a change score suggests an underlying consensus building process in appraisal change. The negative ρ_2 means that, if the appraisals of one's peers become more (less) favorable than expected, given the effects of their intrinsic attributes and the direct effects of social influence on appraisal change, then ego's appraisal change will be less (more) favorable than expected from her attributes and the direct effect of social influence. Rather than being amplified by social influence in a process of polarization, deviations from expected based on the effects of attributes and social influence directly on appraisal change, offset one another among clusters of associates. Put another way, there is clearly no evidence for polarization, as would be the case if ρ_2 were positive and deviations from the expected amount of change were amplified-greater change than expected to a more favorable appraisal if one's associates changed their appraisals more than expected in a favorable direction and more change towards a less favorable appraisal than expected if one's associates changed their appraisals more than expected in a less favorable direction. Absent this consensus/convergence factor, the positive direct influence effect should lead to more divergence in appraisal changes and therefore more variation in 12-month appraisals. However, as presented in (Table 1), there was only a small increase in the standard deviation of the benefit-cost ratio from pre-intervention to the 12-month point.

The capacity of the local network to influence appraisal, when the national advocate could not, brings to mind the importance of the old American idiom asking "How does it play in Peoria?" Accordingly, interventions aimed at changing employer appraisals may need to develop explicit strategies to influence how local networks process information about innovative products. One promising alternative is to complement interventions developed and delivered by nationally recognized opinion leaders with interventions targeting opinion leaders in local employer networks [58,59]. There are challenges in identifying and influencing local opinion leaders; furthermore, the dissemination literature raises questions about whether and to what degree local opinion leaders will adapt standardized messaging to meet local agendas [60].

The study has several limitations to consider. First, although the study analyzed longitudinal data, we cannot establish a causal relationship [18]. It is possible that we observed one direction of a reciprocal process in which employers with common appraisals had more frequent contact with each other to validate their appraisal. Although trials randomizing social network characteristics cannot be meaningfully fielded; future research can increase the support for causality by examining the relationships we demonstrate here in time-lagged models. Second, it is possible that other social network characteristics correlated with frequent contact, which we did not measure in our study, might play a crucial role in influencing appraisal change. In this regard, it is encouraging that we could find no significant relationship between network density and appraisal change. Third, since we do not have data on all individuals in the employer representative's social network, the study lacks complete information on social influences. For example, this RCT collected no data about communications between employer representatives from different regional coalitions. Although those data might not change the main results of our analysis due to relatively infrequent communications, we recommend that future research measure a variety of social network characteristics in the complete network. Lastly, although the randomized control design may reduce the selection biases within the sample, it is possible that employer representatives we studied are more likely to be interested in improving depression in the workplace as they volunteered to participate in the study. Thus, they may be more actively seeking out information on

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the problem and processing information within their social network than a national sample of employers. This potential bias might have overestimated/underestimated the effect of peer influence within the social network in the study. Thus, it will continue to be important for social network analysis to replicate the relationships we observed in multiple and varied samples. The research team notes that the self-selected sample may actually have greater external validity than a sample of representative coalition members to answer the question we pose. Compared to a representative sample, a self-selected sample contains a higher proportion of early innovators. The field needs to understand how peer influence increases dissemination in an early innovator sample to enhance more rapid distribution of evidence-based medical care.

Despite these limitations, the study contributes to the literature in three important ways. First, we demonstrate the impact of peer influence on product appraisal using models which not only control for marketing but also use randomization to control for the unidentified selection biases associated with marketing. Second, the study examined peer influence on appraisal change, rather than appraisal at a single point in time, an important methodological advance in the field to date. Third, the study is the first that simultaneously estimates the impact of two routes of peer influence (network effects and network disturbance) by fitting a general form of the autocorrelation model [30] using empirical data in social network analysis.

Intervention science routinely asks its designers to create interventions that implicitly influence social network appraisals in order to achieve the outcome of interest. Compliance interventions directed towards the patient in all likelihood have to influence the family as well. Dissemination interventions directed towards physicians in all likelihood have to influence other practitioners the physician respects. Perhaps it is time to ask intervention scientists to create interventions that explicitly influence the social network to achieve greater and more sustainable outcomes.

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