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A PROBABILISTIC ANALYSIS FOR MENTAL HEALTH PROBLEMS: EVALUATION OF POLICIES FOR MANAGING DISTRACTED INDIVIDUALS

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Keywords

Mental Health, Probability Models, Policy Evaluation.

Abstract

Mental health problems are among the problems that negatively affect people's daily lives. Depression, post-traumatic stress disorder and anxiety disorder can be given as examples of these problems. The mind of a person exposed to such problems cannot efficiently perform basic functions such as interpreting, synthesizing and understanding what is read. Such problems are addressed with scientific analysis and mathematical models are developed for them. In this paper, we define a class of mental health problems where the goal is to effectively manage distracted individuals that are required to complete specific tasks. The problem has the property that individuals are classified based on the level of distraction and face distraction with certain probability. We perform probabilistic analysis to evaluate different policies that can be implemented by the respective authority to which distracted individuals are responsible for. Numerical experiments reveal that the policy imposing task-related assignments to individuals and offering them the recompense of high-reward and low-penalty significantly outperforms other policies in all the scenarios we examined. This study will pioneer the mathematical modelling of mental health problems.

ZİHİNSEL SAĞLIK PROBLEMLERİ İÇİN OLASILIKSAL ANALİZ: DİKKATİ DAĞILMIŞ BİREYLERİ YÖNETMEYE YÖNELİK POLİTİKALARIN DEĞERLENDİRİLMESİ

Anahtar Kelimeler

Zihinsel Sağlık, Olasılık Modelleri, Politika Değerlendirmesi.

Öz

Zihinsel sağlık problemleri insanın gündelik hayatını olumsuz etkileyen problemler arasında yer almaktadır. Bu problemlere depresyon, travma sonrasi stress bozukluğu ve anksiyete bozukluğu örnek gösterilebilir. Bu tür problemere maruz kalan insanın zihni yorumlama, sentezleme, okuduğunu anlama gibi temel işlevleri verimli bir şekilde gerçekleştiremez. Bu tür problemler bilimsel analizle ele alınır ve bunlar için matematiksel modeller geliştirilmektedir. Bu makalede amacın belirli görevleri tamamlaması gereken dikkati dağılmış bireyleri etkin bir şekilde yönetmek olduğu bir zihinsel sağlık problemleri sınıfını tanımlamaktayız. Problem, bireylerin dikkat dağınıklığı düzeyine göre sınıflandırılması ve belirli bir olasılıkla dikkat dağınıklığı ile karşı karşıya kalma özelliğine sahiptir. Dikkati dağılmış bireylerin sorumlu olduğu ilgili otorite tarafından uygulanabilecek farklı politikaları değerlendirmek için olasılıksal analiz yapmaktayız. Sayısal deneyler, bireylere görevleriyle ilgili atamaları empoze eden ve onlara yüksek ödül ve düşük ceza karşılığı sunan politikanın, incelediğimiz tüm senaryolarda diğer politikalardan önemli ölçüde daha iyi performans gösterdiğini ortaya koymaktadır. Bu çalışma zihinsel sağlık problemlerinin matematiksel olarak modellemesine öncülük edecek niteliktedir.

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A PROBABILISTIC ANALYSIS FOR MENTAL HEALTH PROBLEMS: EVALUATION OF POLICIES FOR MANAGING DISTRACTED INDIVIDUALS

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Highlights

- We study a class of mental health problems.
- We perform probabilistic analysis to evaluate different policies.
- The policy imposing task-related assignments to individuals outperforms other policies.

Purpose and Scope

The goal of this research is to examine different policies that can be applied to distracted individuals.

Design/methodology/approach

A probabilistic model was developed for a class of mental health problems. The objectives were achieved by comparinf different policies on the problem studied. Subject scope of the paper is mathematical model for mental health problems.

Findings

Numerical results reveal that offering incentive through high reward is highly effective for individuals in the face of distraction resulting from having mental health problems. In addition, the impact of this policy is higher in the mild-response case than in the severe-response case.

Research limitations/implications

The values of parameters such as distraction probability for each patient type along with success and failure probabilities for each case are determined somewhat arbitrarily, which is the main limitation of the paper. As a future research, a dynamic feature can be added to the model in terms of decision making process. In other words, the duration for the underlying task can be divided into stages such as days.

Practical implications

The policy imposing task-related assignments to individuals and offering them the recompense of high-reward and low-penalty significantly outperforms other policies in all the scenarios we examined.

Originality

The paper is unique in terms of the probaility model developed. The fact that various policies are examined for a class of mental health problems is new in the paper.

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1. Introduction

Distraction is one of the issues caused by mental-health related diseases such as depression and anxiety disorders. Due to its adverse effects, individuals experiencing distraction are unable to perform daily activities efficiently, thereby wasting precious resources such as time and energy.

The main reason for distraction can be attributed to being exposed to negative influence. In such a state, the mind's attention is diverted from the reality to past events or imaginations that may include people that were distractors in the past. As a result, individuals facing distraction cannot entirely focus on their tasks, which may also cause emotional weaknesses such as misery and stress. In this context, distraction is essentially the change in the state of mind that generally causes delay in its operations. To illustrate, because of struggling with distraction, an individual may not be able to meet the deadline of the underlying task. Further, increase in the severity of distraction generally increases the level of insufficiency in completing tasks.

Distraction can be said to occur in two days: 1) the occupation of the mind with the past undesired events or people that sometimes may cause fear or anxiety for future, 2) due to staggering events such as a tragic accident or death of a close relative. In both cases, the mind is influenced negatively, not being able to effectively process information and to operate efficiently. Further, it is fair to state that distraction is inevitable in any kind of mental health problems such as anxiety disorders, depression, and rumination.

In this paper, we investigate the effectiveness of different strategies implemented for individuals struggling with various levels of distraction, from the perspective of the respective authority. We specifically analyze situations where an individual experiencing distraction is expected to follow the instructions/orders of the underlying authority and has to complete a specific task within a given deadline. For example, an individual can be an adolescent while the respective authority can be his/her parents who have various expectations from their child. Consider another situation where a doctoral student has to follow the instructions of his (her) supervisor throughout his doctoral studies. Such a scenario can be related to even a Covid-like pandemic (or any disaster such as earthquake or flood) in the sense that individuals having the anxiety of being infected with pandemic are expected to follow the authority, which is the respective government. In this regard, we consider certain policies that can be implemented by the authority such as imposing complete freedom, imposing certain instructions/rules along with rewards and penalties that will be incurred, depending on whether the individual is able to complete the task.

We perform a probabilistic analysis to assess the effectiveness of specific policies under diverse scenarios determined by factors such as the severity of distraction. Under certain assumptions, we demonstrate that the assignment-imposing policy with high rewards and low penalties significantly outperforms other policies in all scenarios. Unsurprisingly, our results reveal that the freedom policy performs quite poorly as compared to other policies, as it has no direct control on the actions of individuals confronting distraction.

The paper is structured as follows. Section 2 discusses the related literature in mental health. In Section 3, we define a class of mental health problems centered on distraction and provide the basics of our probabilistic model. We provide the details about experimental settings and numerical results in Section 4. Finally, Section 5 contains discussion on our work and concludes.

2. Literature Survey

Literature on mental health-related problems is quite rich (interested readers are referred to Repper and Carter (2020), Frasquilho et al. (2016), Bogic et al. (2015), Pragati et al. (2021), Richter and Dixon (2023)). Here, we briefly review the related literature focusing mainly on articles published in the last decade in order to emphasize the importance of these problems.

Lim et al. (2018) investigated the prevalence of depression observed in a number of countries between 1994 and 2014, exploring the variations in prevalence. The authors emphasize that their analysis benchmarks the prevalence of depression. In another study, Albert (2015) analyzed the reason why depression is more prevalent in women. The author points out the fact that depression is the highest global burden of disease and then conjectures that it will be the leading cause of disease burden within nearly ten years.

Lepine and Briley (2011) examine the impact of depression on the quality of life of the subject and how depression negatively affects the family of the depressed patient as well as society. Galbraith et al. (2021) emphasize the adverse situations of doctors caused by the additional pressure placed by the COVID-19 disease. The authors stress that strong leadership and support for doctors and their families during the COVID-19 disease must be provided by the respective authorities.

Another study conducted by O'connor et al. (2021) discusses the adverse effects of COVID-19 on the population's mental health. The objective of this study is to analyze "trajectory of mental health and well-being" during a particular lockdown period in adults in the UK. Their results reveal that the initial phase of the COVID-19 pandemic affected the mental health and well-being of the UK adult population.

Poli et al. (2020) discusses the impact of good mental health on young people with and without mental disorders, stating that this topic received little empirical research attention. The authors provide a critique of the available operationalizations for good mental health.

In their paper, Evans e al. (2018) discuss the mental health problems faced by graduate students across the globe. The authors conducted an extensive survey about anxiety and depression through tools such as social media and direct email. Their results indicate that graduate students are much more prone to depression and anxiety as compared to public.

Mikkelsen et al. (2017) focus on the positive effects of exercise on anxiety, stress, and depression via physiological and biochemical mechanisms such as endorphins and mitoochondria. The authors state that, in line with the distraction hypothesis and the self-efficacy hypothesis, the effects of exercise on mood states are influenced by psychological mechanisms.

The mental health problems experienced by college students and substance use are addressed in Pedrelli et al. (2015). The authors contribute to these problems in a variety of ways such as through the description of the prevalence of psychiatric and substance use problems in college students, and summarizing the attributes of mental health problems among college students.

Hameed et al. (2024) study the impact of financial strain that arises from job loss due to COVID-19. One of the authors' findings is that there is a strong negative relationship between financial strain and subjective well-being. Further, Reed et al. (2023) investigate the impacts of the COVID-19 pandemic on the mental health of young adults. Their results reveal that such a relationship is complex, and that distress and well-being tend to increase across the period of the study.

Rodriguez et al. (2024) study the relationship between sports practice and psychological well-being. The authors review articles about this topic to explore pathways that link physical engagement in sports to its impacts on mental health. In a review article, Somi et al. (2022) conduct a systematic review for mental disorders. The authors also investigate median age at onset of specific disorders. Further, Xiong et al. (2020) investigate the impact of COVID-19 on mental health, focusing on the general population. Their results reveal that high rates of symptoms of anxiety, depression, psychological distress, etc. are reported during the COVID-19 pandemic countries such as Spain, Italy, US, and Turkey.

In a related work, Göçgün (2020) defines a mental health problem where the decision is how to react during depression from the perspective of individuals experiencing this disease. Modeling the problem as a Markov decision process with several assumptions, the author provides the optimal solution to this problem and discusses the performances of two easy-to-use decision rules.

Although diverse problems in mental health are addressed in the literature, there is no study that provides a probabilistic analysis of adverse effects of distraction within the context of mental health. Our work is an attempt to close this gap and to direct mental health research towards the impact of distraction on society.

3. Material and Method

We define a class of mental health problems where the goal is to effectively manage an individual who is likely to be distracted due to experiencing a traumatic event such as violence or divorce, and has to complete a task by a given deadline. Examples of such tasks include but not limited to the entire process of a graduate study, a project assigned by an institution to its employees, and a capstone project assigned to college students. In this setting, completing a task can be generalized as fulfilling specific requirements related to the underlying task. Further, individuals are distracted with a certain probability and are classified based on how likely they are prone to distraction.

The likelihood of an individual completing his (her) task is affected by whether he is distracted, and (if so) the level of distraction he faces: high, medium, or low levels. That is, while a group of individuals may belong to highly distracted category because of factors such as low education and low income levels, another group can be viewed as lowly distracted people owing to factors such as having high education and high intellectual levels. We consider the following three outcomes when the deadline of the respective task is reached: completion of the task, failure, or an incomplete task. Having an incomplete task differs from failure of the task in that in the former case the expectations of the authority about the task is partially completed.

We consider three scenarios that differ in the distribution of individuals belonging to the following groups: high, medium, and low levels of distraction. The following policies are evaluated through probabilistic analysis.

No-assignment Policy (Pl-1) This policy does not impose any task-related assignment to the distracted individual, thereby providing him/her freedom in the way he (she)completes the task.

Assignment Policy (Pl-2) Unlike the no-assignment policy, this policy requires the individual to complete specific assignments without incurring any reward or penalty. Examples of such assignments include any kind of sub-tasks that would expedite the completion of the entire task.

Assignment Policy with High-reward and Low-penalty (Pl-3) In order to increase the motivation of the individual and hence to reduce the effect of distraction, this policy imposes the individual an assignment(s) and incurs high reward and low penalty when the outcome of the task is success and failure, respectively. If the outcome is an incomplete task (i.e., neither success nor failure), then there will be no recompense.

Assignment Policy with Low-reward High-penalty (Pl-4) This policy aims to reduce the effect of distraction by imposing the individual an assignment(s) and incurring high penalty and low reward when the outcome is failure and success, respectively.

The following assumptions are made for the abovementioned mental health problem.

- The probability of the underlying task being successfully completed decreases with an increase in the level of distraction. This is due to the fact that when the level of distraction increases, it becomes more difficult to complete the task.
- The probability of the underlying task being failed increases with an increase in the level of distraction. This can be explained through the above reasoning.
- The probability of the underlying task being successfully completed is for Pl-1 is less than or equal to that for other policies. The reason is due to the fact that a given assignment as well as a motivation through reward and penalty would increase the likelihood of completing the task.

We perform probabilistic analysis for determining total number of successes, failures, and ongoing tasks using the abovementioned policies. Specifically, one million individuals were considered that are classified on the basis of the distribution of distraction levels. We consider three scenarios determined by the distribution of distraction levels; namely, the base-case scenario, the worst-case scenario and the plausible scenario (details about those scenarios are given in Section 4).

4. Experimental Results

4.1. Experimental Design

As stated earlier, we consider the following scenarios in our probabilistic analysis: 1) the base-case scenario, 2) the worst-case scenario, and 3) plausible scenario.

For the base-case scenario, the distribution for individuals who are prone to high, mild, and low distraction is set to (0.4,0.4,0.2) respectively, implying that the percentages of those who would be highly and mildly affected by distraction are both 0.4. The distraction-level distributions for the worst-case scenario and the plausible scenario are set to (0.7,0.1,0.2) and (0.1, 0.7, 0.2), respectively. Note that the percentage of those who have high potential in being severely affected by distraction is much higher in the worst-case scenario.

The probability of being distracted is first assumed to be the same for each individual type (i.e, highly, mildly, and lowly distracted people). This value is set to 0.8, 0.4, and 0.2. We then analyzed the situation where the underlying probability differs in individual type. We specifically considered a severe case and mild case, which differ in the underlying probability values. The distributions for the severe case and mild case are set to (0.75, 0.5, 0.25) and

(0.5, 0.25, 0). For example, in the severe case, the probability that an individual from highly-distracted type will be distracted upon a staggering event is 0.75, whereas this value is 0.5 in the mild case.

With regard to the responses of individuals that face distraction, we consider two cases: 1) severe response, 2) mild response. In the severe response case, the probability that an individual from highly-distracted type will successfully complete the task when Pl-1, Pl-2, Pl-3, or Pl-4 is implemented is set to 0,0,0.33,0, respectively. In words, such a person, who is highly influenced when she experiences distraction, is assumed to end up with a failure with certainty under all policies except Pl-3. The probability of failing the task in the same case is set to 0.67, 0.33, 0, and 0 for Pl-1 through Pl-4, respectively. (note that in this case, the probability of the task being incomplete but not failed for a highly-distracted individual for, say, Pl-1, is 1-0.67-0 = 0.33.) The reason is due to the intuition that when the distracted mind is occupied by a task-related assignment and has the awareness of a recompense that will be faced upon reaching the task deadline, the level of focus for the task will increase and hence the likelihood of failure will decrease remarkably.

On the other hand, the success and failure probability values for a distracted individual from the mildly-distracted type (expressed in vector form) are set to (0,0.33,0.67,0.33) and (0.33,0,0,0), respectively (e.g., the first element of each vector corresponds to the respective probability value when Pl-1 is carried out). The reason is, for example, that, as the individual will be mildly influenced by distraction, it is reasonable to assume that the likelihood of him failing the task will be 0 under any policy except Pl-1. Similarly, because of the mild effect of distraction on him, the probability of him completing the task is significantly higher under Pl-3 than that for any other policy. As for the distracted individual from the lowly-distracted type, the success and failure probabilities are set as (0.33,0.67,1,1) and (0,0,0,0). The assumption that he will never fail the task with certainty under any policy is due to low effect of distraction on the individual.

The success and failure probabilities in the mild response case are set to the following values:

- For a highly-distracted individual: (0,0,0.45,0.13), (0.5,0.2,0,0)
- For a mildly-distracted individual: (0,0.45,0.8,0.45), (0.15,0,0,0)
- For a lowly-distracted individual: (0.5,0.8,1,1), (0,0,0,0)

For example, a highly-distracted individual will complete the task with probabilities of 0.45 and 0.13 under Pl-3 and Pl-4, respectively.

We illustrate the way to obtain results such as number of successes below.

- S1: Distribution of distraction proneness. S1 = 1 for the best, S1 = 2 for the worst, and S1 = 3 for the plausible scenario.
- S2: Dependence structure of distraction probabilities on distraction proneness. S2 = 1 for independent with all-0.8 prob, S2 = 2 for independent with all-0.4 prob, S2 = 3 for independent with all-0.2 prob, S2 = 4 for severe case with conditional prob.s (0.75,0.5,0.25), and S2 = 5 for mild case with conditional prob.s (0.5,0.25,0).
- S3: Response levels to distraction in task completion (S3 = 1 for the severe response and S3 = 2 for the mild response)

D: The choice of assignment/reward policy. D = 1 for Pl-1, D = 2 for Pl-2, D = 3 for Pl-3, and D = 4 for Pl-4.

Input random variables:

- X1: The category of a random individual in distraction proneness. X1 = 1 for high, X1 = 2 for mild, and X1 = 3 for low distraction. X1 follows a conditional PMF on S1.
- X2: The status of being distracted for a random individual. X2 = 1 for someone who gets distracted, X2 = 2 for someone who avoids being distracted. X2 follows a conditional PMF on X1 and S2, and finally, a discretely distributed output random variable:
- Y: The response of a random individual in task completion. Y = 1 for success, Y = 2 for failure, and Y = 3 for an incomplete task. Y has a conditional PMF on X1, X2, S3, and D.

P {Y = 1|S1 = 1, S2 = 1, S3 = 1, D = 1} = sum(i in 1..3) sum (j in 1..2) P {X1 = i|S1 = 1} P {X2 = j|X1 = i, S2 = 1} P {Y = k|X1 = i, X2 = j, S3 = 1, D = 1} = 0.4 × 0.8 × 0 + 0.4 × 0.2 × 1 + 0.4 × 0.8 × 0 + 0.4 × 0.2 × 1 + 0.2 × 0.8 × 0.33 + 0.2 × 0.2 × 1 = 0.2528.

Due to the above calculation, the number of successes for PL-1 is 253 (see Table 1).

It is worth mentioning that the values of parameters such as the probability of being distracted are set arbitarily. This does not cause any issue in our analysis because we are interested in relative comparison of policies, which is robust to the values of such parameters. Further, parameter values are determined by considering intuitive assumptions about the problem setting, and hence do not have remarkable impact on relative comparison of policies.

4.2. Results

The results of our probabilistic analysis are presented in tables 1 through 8 (for instance, 253 actually refers to 253000 out of 100000, which is equivalent to 253 out of 1000). In particular, tables 1 to 4 provide number of successes and number of failures for each scenario obtained for the severe-response case; whereas the remaining tables provide the same statistics for the mild-response case. $\vec{P}_{dst}$ represents a distraction probability vector for individuals from highly, mildly, and lowly distracted types. Further, P.I.(Pl-i), $i = 2,3,4$ stands for percentage improvement of Pl-i over Pl-1. Finally, B.C., Sc-2, and Sc-3 refer to the base-case, the worst-case, and the plausible scenarios, respectively.

One of the prominent results is that, Pl-1 (no-assignment policy) performs significantly worse than other policies for any given parameter combination, especially when the level of distraction is high (see tables 1 and 2). Additionally, regardless of the type of scenario and the distraction probability distribution, Pl-3 (the assignment policy with high reward and low penalty) significantly outperforms other policies. To illustrate, average percentage improvement for the Pl-3 over Pl-1 in the same-distraction-probability scenario for the severe-response case is around 169%, whereas the respective average percentage improvement for the Pl-4 over Pl-1 is around 105% (see Table 1). As expected, the next best policy is Pl-4 (the assignment policy with low reward and high penalty), as the strategy of imposing high penalty upon a failure is generally more effective than the assignment with no-penalty policy. What is more, the smaller the probability of being distracted is, the smaller the impact of policies 2,3, and 4 will be (see, for instance, tables 1 and 2).

Further, the impact of Pl-3 is higher in Scenario-3 (the plausible scenario) when distraction probability is the same for each individual type; whereas this policy is more effective in Scenario-2 (the worst-case scenario) in more realistic situations where the distraction probability varies over individual type (see tables 1 and 2). As for Pl-2 and Pl-4, they are always the most effective in the plausible scenario. Further, in terms of number of failures, Pl-2 and Pl-4 perform the same in the severe-response case (see tables 3 and 4); whereas the results for the mild-response case reveal that Pl-4 is much more effective than Pl-2. It is also worth noting that the percentage improvements with regard to number of successes as well as failures are higher in the mild-response case than those in the severe-response case (see tables 2, 6, 4, and 8).

Table 1. Number of successes for the (severe-response) case where probability of being distracted are 0.8, 0.4, and 0.2 for each type of individual

Scenario	$\vec{P}_{dst}$	Pl-1	Pl-2	Pl-3	Pl-4	P.I.(Pl-2)	P.I.(Pl-3)	P.I.(Pl-4)
B.C.	(0.8,0.8,0.8)	253	413	680	520	63.2	168.8	105.5
Sc-2	(0.8,0.8,0.8)	253	334	599	400	32.0	136.8	58.1
Sc-3	(0.8,0.8,0.8)	253	493	762	640	94.9	201.2	153.0
average		**253**	**413.3**	**680.3**	**520**	**63.4**	**168.9**	**105.5**
B.C.	(0.4,0.4,0.4)	626	706	840	760	12.8	34.2	21.4
Sc-2	(0.4,0.4,0.4)	626	666	799	700	6.4	27.6	11.8
Sc-3	(0.4,0.4,0.4)	626	746	880	820	19.2	40.6	31.0
average		**626**	**706**	**839.6**	**760**	**12.8**	**34.1**	**21.4**
B.C.	(0.2,0.2,0.2)	813	852	919	879	4.8	13.0	8.1
Sc-2	(0.2,0.2,0.2)	813	833	899	849	2.5	10.6	4.4
Sc-3	(0.2,0.2,0.2)	813	872	940	909	7.3	15.6	11.8
average		**813**	**852.3**	**919.3**	**879**	**4.8**	**13.1**	**8.1**

Table 2. Number of successes for the (severe-response) case where probability of being distracted varies over types of individuals

Scenario	$\vec{P}_{dst}$	Pl-1	Pl-2	Pl-3	Pl-4	P.I.(Pl-2)	P.I.(Pl-3)	P.I.(Pl-4)
B.C.	(0.75,0.5,0.25)	466	550	733	600	18.0	57.3	28.8
Sc-2	(0.75,0.5,0.25)	391	425	632	450	8.7	61.6	15.1
Sc-3	(0.75,0.5,0.25)	541	674	834	750	24.6	54.2	38.6
average		**466**	**550**	**733**	**600**	**17.1**	**57.7**	**27.5**
B.C.	(0.5,0.25,0)	700	733	833	750	4.7	19.0	7.1
Sc-2	(0.5,0.25,0)	625	633	757	637	1.3	21.1	1.9
Sc-3	(0.5,0.25,0)	774	832	908	862	7.5	17.3	11.4
average		**700**	**733**	**833**	**750**	**4.5**	**19.1**	**6.8**

Table 3. Number of failures for the (severe-response) case where probability of being distracted are 0.8, 0.4, and 0.2 for each type of individual

Scenario	$\vec{P}_{dst}$	Pl-1	Pl-2	Pl-3	Pl-4	P.I.(Pl-2)	P.I.(Pl-3)	P.I.(Pl-4)
B.C.	(0.8,0.8,0.8)	319	105	0	105	67.1	100	67.1
Sc-2	(0.8,0.8,0.8)	400	184	0	184	54	100	54
Sc-3	(0.8,0.8,0.8)	237	26	0	26	89	100	89
average		**318.7**	**105**	**0**	**105**	**70**	**100**	**70**
B.C.	(0.4,0.4,0.4)	159	52	0	52	67.3	100	67
Sc-2	(0.4,0.4,0.4)	200	92	0	92	54	100	54
Sc-3	(0.4,0.4,0.4)	119	13	0	13	89.1	100	89.1
average		**159.3**	**52.3**	**0**	**52.3**	**70.1**	**100**	**70.1**
B.C.	(0.2,0.2,0.2)	80	26	0	26	67.5	100	67.5
Sc-2	(0.2,0.2,0.2)	100	46	0	46	54	100	54.0
Sc-3	(0.2,0.2,0.2)	59	6	0	6	89.8	100	89.8
average		**79.7**	**26**	**0**	**26**	**70.4**	**100**	**70.4**

Table 4. Number of failures for the (severe-response) case where probability of being distracted varies over types of individuals

Scenario	$\vec{P}_{dst}$	Pl-1	Pl-2	Pl-3	Pl-4	P.I.(Pl-2)	P.I.(Pl-3)	P.I.(Pl-4)
B.C.	(0.75,0.5,0.25)	266	98	0	98	63.2	100	63.2
Sc-2	(0.75,0.5,0.25)	367	172	0	172	53.1	100	53.1
Sc-3	(0.75,0.5,0.25)	165	24	0	24	85.5	100	85.5
average		**266**	**98**	**0**	**98**	**67.2**	**100**	**67.2**
B.C.	(0.5,0.25,0)	166	65	0	65	60.8	100	60.8
Sc-2	(0.5,0.25,0)	242	115	0	115	52.5	100	52.5
Sc-3	(0.5,0.25,0)	91	16	0	16	82.4	100	82.4
average		**166**	**65**	**0**	**65**	**65.2**	**100**	**65.2**

Table 5. Number of successes for the (mild-response)case where the probability of being distracted are 0.8, 0.4, and 0.2 for each type of individual

Scenario	$\vec{P}_{dst}$	Pl-1	Pl-2	Pl-3	Pl-4	P.I.(Pl-2)	P.I.(Pl-3)	P.I.(Pl-4)
B.C.	(0.8,0.8,0.8)	280	472	760	546	68.6	171.4	95.0
Sc-2	(0.8,0.8,0.8)	280	364	676	469	30.0	141.4	67.5
Sc-3	(0.8,0.8,0.8)	280	580	844	623	107.1	201.4	122.5
average		**280**	**472**	**760**	**546**	**68.6**	**171.4**	**95**
B.C.	(0.4,0.4,0.4)	640	736	880	773	15.0	37.5	20.8
Sc-2	(0.4,0.4,0.4)	640	681	838	734	6.4	30.9	14.7
Sc-3	(0.4,0.4,0.4)	640	790	922	811	23.4	44.1	26.7
average		**640**	**735.7**	**880**	**772.7**	**14.9**	**37.5**	**20.7**
B.C.	(0.2,0.2,0.2)	819	867	940	886	5.9	14.8	8.2
Sc-2	(0.2,0.2,0.2)	819	840	918	867	2.6	12.1	5.9
Sc-3	(0.2,0.2,0.2)	819	894	961	905	9.2	17.3	10.5
average		**819**	**867**	**939.7**	**886**	**5.9**	**14.7**	**8.2**

Table 6. Number of successes for the (mild-response) case where probability of being distracted varies over types of individuals

Scenario	$\vec{P}_{dst}$	Pl-1	Pl-2	Pl-3	Pl-4	P.I.(Pl-2)	P.I.(Pl-3)	P.I.(Pl-4)
B.C.	(0.75,0.5,0.25)	475	580	795	629	22.1	67.4	32.4
Sc-2	(0.75,0.5,0.25)	400	437	701	516	9.3	75.3	29.0
Sc-3	(0.75,0.5,0.25)	550	722	889	742	31.3	61.6	34.9
average		**475**	**579.7**	**795**	**629**	**20.9**	**68.1**	**32.1**
B.C.	(0.5,0.25,0)	700	745	870	771	6.4	24.3	10.1
Sc-2	(0.5,0.25,0)	625	636	802	682	1.8	28.3	9.1
Sc-3	(0.5,0.25,0)	774	853	937	860	10.2	21.1	11.1
average		**699.7**	**744.7**	**869.7**	**771**	**6.1**	**24.6**	**10.1**

Table 7. Number of failures for the (mild-response) case where probability of being distracted are 0.8, 0.4, and 0.2 for each type of individual

Scenario	$\vec{P}_{dst}$	Pl-1	Pl-2	Pl-3	Pl-4	P.I.(Pl-2)	P.I.(Pl-3)	P.I.(Pl-4)
B.C.	(0.8,0.8,0.8)	207	63	0	0	69.6	100	100
Sc-2	(0.8,0.8,0.8)	291	111	0	0	61.9	100	100
Sc-3	(0.8,0.8,0.8)	123	16	0	0	87	100	100
average		**207**	**63.3**	**0**	**0**	**72.8**	**100**	**100**
B.C.	(0.4,0.4,0.4)	103	32	0	0	68.9	100	100
Sc-2	(0.4,0.4,0.4)	145	55	0	0	62.1	100	100
Sc-3	(0.4,0.4,0.4)	61	8	0	0	86.9	100	100
average		**103**	**31.7**	**0**	**0**	**72.6**	**100**	**100**
B.C.	(0.2,0.2,0.2)	51	16	0	0	68.6	100	100
Sc-2	(0.2,0.2,0.2)	73	28	0	0	61.6	100	100
Sc-3	(0.2,0.2,0.2)	30	4	0	0	86.7	100	100
average		**51.3**	**16**	**0**	**0**	**72.3**	**100**	**100**

Table 8. Number of failures for the (mild-response) case where probability of being distracted varies over types of individuals

Scenario	$\vec{P}_{dst}$	Pl-1	Pl-2	Pl-3	Pl-4	P.I.(Pl-2)	P.I.(Pl-3)	P.I.(Pl-4)
B.C.	(0.75,0.5,0.25)	179	59	0	0	67	100	100
Sc-2	(0.75,0.5,0.25)	269	104	0	0	61.3	100	100
Sc-3	(0.75,0.5,0.25)	89	15	0	0	83.1	100	100
average		**179**	**59.3**	**0**	**0**	**70.5**	**100**	**100**
B.C.	(0.5,0.25,0)	114	39	0	0	65.8	100	100
Sc-2	(0.5,0.25,0)	178	69	0	0	61.2	100	100
Sc-3	(0.5,0.25,0)	51	10	0	0	80.4	100	100
average		**114.3**	**39.3**	**0**	**0**	**69.1**	**100**	**100**

5. Result and Discussion

The results in Section 4 reveal that offering incentive through high reward (Pl-3) is highly effective for individuals in the face of distraction resulting from having mental health problems. In addition, the impact of this policy is higher in the mild-response case than in the severe-response case, which can be explained as follows. When the level of distraction does not have a significant effect on individuals' behaviors (i.e., in the mild-response case), incentives offered to them leads to relatively higher success. To illustrate, the average difference between the two cases in the type-based distraction scenario for Pl-1 in terms of number of successes is 9 (466 vs. 475), whereas it is 62 (733 vs. 795) for Pl-3 (see tables 2 and 6).

Undoubtedly, the values of parameters such as distraction probability for each patient type along with success and failure probabilities for each case are determined somewhat arbitrarily. Indeed, the outputs of our model, which are number of successes, failures, and incomplete tasks are solely dependent on those parameters. It should however be noted that our goal is to identify relative comparisons of the policies we consider in this study. Thus, the implications we derived in Section 4 would still be valid for other combinations of parameter values.

While our results indicate that Pl-3 is the most effective policy to be implemented upon individuals that are prone to distraction, in reality, this may not always be the case. The reason is that the underlying authority may have limited budget that prevents it from providing incentives to its people. For that case, Pl-4 (the low-reward-high-penalty) will have the highest impact on the performances of the respective individuals. It is also worth noting that strategies aiming to reduce the level of distraction through ways such as education is also nearly as effective as Pl-3. To illustrate, for Pl-1, average number of successes is increased from 466 to 700 when the probability vector of distraction values reduces from (0.75,0.5,0.25) to (0.5,0.25,0). However, if the policy is changed to Pl-3 without any change in the distraction probability values, average number of successes will be 733 (see Table 2).

Our work is an attempt to shed light on strategies that can be used to mitigate the effects of distraction in the context of mental health. Specifically, we defined a class of mental health problems where individuals face distraction due to having experienced a tragic event and at the same time are required to complete a task. We modeled the problem using probability under certain assumptions such as no budget limitation, and evaluated a few policies such as those imposing individuals assignments through which they are recompensed based on whether the underlying task is completed or failed. As stated earlier, our numerical experiments reveal that the no-assignment policy, on average, performs significantly worse, and the high-reward-low-penalty assignment policy performs significantly better than other policies.

This research can be extended as follows. A dynamic feature can be added to the model in terms of decision making process. That is, the duration for the underlying task can be divided into stages such as days. The decision to be made by the authority would be which policy to implement after observing the state of the individual. This leads to a dynamic policy rather than a fixed policy that is implemented throughout the entire duration for the underlying task. Further, additional probability vectors for distraction can be tested to have more insights on how the percentage improvements are affected by the probability of being distracted.

Conflict of Interest

No conflict of interest was declared by the author.

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