Algorithmic Patient Matching in Peer Support Systems for Hospital Inpatients

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Peer support in inpatient portal systems can help patients to manage their hospital experiences, namely through social modeling of similar patients' experiences. In this position paper, I will begin by providing a theoretical foundation of social modeling and peer matching. Then I will present matching strategies for algorithmic tools to match patients by their similarities, as well as the challenges and consequences that will surface when such a system is deployed in the wild. These technosocial complexities show that algorithmic matching in this context is non-trivial. Finally, based on the evidence and theories known thus far, I will present two recommendations on how to algorithmically match patient that will support social modeling, align with human cognition, and reduce the risk of injustices in clinical settings.

CCS Concepts: • **Human-centered computing → Collaborative and social computing**.

Additional Key Words and Phrases: patient portals, peer-support, social cognitive theory, algorithmic matching

1 INTRODUCTION

Hospital stays are often difficult for patients due to the illness as well as the stressful and information-poor nature of the hospital environment [12, 14]. Although hospitals' key expertise is providing clinical care, patients also require emotional and informational support to help them navigate their time of receiving care in the hospital [13].

Inpatient portals have the potential to help patients get the support they need from their peers who also stay in the hospital. Haldar et al.'s [12] evaluation of an inpatient portal shows how the peers in such a portal can provide support, namely emotional and informational support (e.g., adjusting to the hospital, learning about communicating with providers, understanding care, and preventing medical errors). From the perspective of Social Cognitive Theory, this peer support appeared to impact self-efficacy [2–4]. Specifically, the self-efficacy to navigate inpatient experiences.

In this paper, I will first discuss the benefits of inpatient portals in providing peer support using Social Cognitive Theory as a theoretical lens, which include social modeling specifically. I will also discuss how algorithmic tools can make social modeling more effective by matching similar patients by their features. Then, I will discuss how three kinds of patient features can be used in algorithmic matching tools. After that, I will discuss the challenges and the negative consequences of using algorithmic matching from the perspective of fairness and ultimately social justice. Finally, I will conclude this paper by offering two human-centered strategies for algorithmic patient matching.

2 SOCIAL COGNITIVE THEORY (SCT)

SCT is a well-established theory that shows human cognition and behavior are influenced by and influencing their social environment [2–4]. According to SCT, self-efficacious people are more optimal in performing the behavior of interest. Therefore, peer-support in inpatient portals can enhance patients' self-efficacy in navigating their hospitalization experiences (i.e., the behavior).

Self-efficacy is a domain-specific belief that is developed over time. Four kinds of information enhance self-efficacy, namely mastery experiences, vicarious learning, verbal persuasion, and emotional states [2, p 399]. As evident in Haldar et al.'s work, inpatient portals support self-efficacy in two ways [13]. First, they provide emotional support that enhances emotional states. Second, they provide a space for social modeling (i.e., vicarious learning) on how to adjust to the hospital, communicate with providers, and understand care. Given the importance of emotional states and social modeling in shaping one's behavior, SCT is a potential framework to understand and enhance inpatient portals; and ultimately enhance hospital patients' wellbeing [21].

SCT also emphasized that social modeling is more effective if we observe models whom we perceived as similar [2–4]. The tendencies to focus on similar models is because our actions are readily facilitated and constrained by our physical and social environment, thus observing models who are similar to us assures that we can closely replicate the models' behavior.

Social modeling in technologies has been examined by prior Human-Computer Interaction (HCI) studies. In my study on a social app for physical activity promotion among families with low-socioeconomic status, I found that stories communicated through digital health apps can support people's health in two ways [26]. First, stories provide informational support in terms of the steps needed to develop healthy behavior, which resonates with prior work in healthy eating [8]. Second, stories support people to develop a sense of commonality, echoing prior HCI studies on multiple domains. For example, sharing stories can validate people's health experiences [1] and also challenges false societal norms about women's reproductive health [23].

I also found that families prefer to model other families who are similar to them in terms of the impediments that they faced (e.g., similar in the number of children, neighborhoods). More importantly, every family had its own set of variables that helped them determine similarity. For instance, the number of children may be useful to determine similarity for one family but not in other families.

In short, from the perspective of SCT, peer-support in inpatient portals can enhance patients' wellbeing by enhancing self-efficacy through the exchange of emotional and informational support. However, peer-support can be more effective if the patient can feel more similar to other patients who shared informational support.

3 ALGORITHMICALLY MEDIATED SOCIAL MODELING

Algorithmic tools (e.g., machine learning) can make peer support more effective by matching or curating peer's content to match the patient's characteristics, especially that content will grow over time [16]. I will describe an example of such a system below.

Suppose that there are patients $p_i \in P$ and also stories $s_j \in S$ told by the patients. Every patient p_i has a set of features $x_{i,k}$ (e.g., demographic information, ability information, story keywords). Consequently, every story also has a set of features $y_{j,k}$ based on the patient p_j who told the story. The goal of an algorithmic matching tool is to match or curate stories for an *observer* $\in P$ based on their feature similarities with the pool of stories S told by *models* $\in P$.

Here, I will present the ways to operationalize the notion of being "similar", which will guide how to design such a matching or curation algorithm. These notions of similarity are material, interpretative, and experiential features.

Material features are similarities that are often readily observable, such as gender and race. For example, in a study with breast cancer patients, Rogers et al. found that having a role model with breast cancer can encourage exercise self-efficacy [25]. Similarly, in a review paper on social modeling for healthy eating, Cruwys et al. found that gender, age, or weight similarities appeared to enhance social modeling [9]. In short, material features are the easily observable characteristics that inform the observer to determine whether they can replicate the models' behavior.

Interpretative features are similarities that are perceived rather than directly observed, such as abilities [11]. In contrast to material features that are readily observable, interpretative features require the observer to interpret their abilities and the abilities of the model. For example, in a social modeling study among students, Braaksma et al. found that weak students benefit from observing weak models, whereas better students benefit from strong students [5]. In some cases, both material and interpretative features work hand-in-hand, as in Meaney et al.'s study [22]. They found that women learn new skills better by observing models of similar gender or similar abilities.

Experiential features are similarities based on the shared experiences and also shared societal barriers produced by the features. For example, in a preliminary study by Hartzler et al., found that patients preferred using mentors' stories to select a mentor [16]. Similarly, in my family fitness study, I found that parents preferred barrier information (e.g., neighborhood, number of children) to determine whether they can replicate their peers behavior [26]. In a similar vein, Daskalova et al.'s study on cohort-based sleep recommendations tool also advocated for the need to help users identify cohorts who faced similar barriers in getting a healthy sleep [10].

Using these three notions of similarities, algorithmic patient matching tools can match an observing patient with their model peers. However, although such tools can effectively help patients to enhance their self-efficacy through social modeling, using algorithmic approaches to mediate social modeling could have adverse consequences in real-world deployment, which I will discuss next.

4 CHALLENGES OF ALGORITHMICALLY MEDIATED SOCIAL MODELING

Although algorithmic peer matching can make peer support in inpatient portals more effective, it is not without potential negative consequences when deployed in the wild. Assuming that the baseline challenges are addressed (e.g., the patient consented to share their identities into the patient portal and content moderation is optimal to prevent medical misinformation), other challenges and consequences can still arise: (a) social categorization, (b) experience reduction, and (c) information segregation. Ultimately, these three challenges and consequences highlight that algorithmic matching is a non-trivial problem because of the societal complexities of matching.

(a) The challenge of social categorization arose because human infer the meanings of other people's actions based on the observable identities [18] and this inference is intersectional and dynamic [24]. In the context of algorithmic patient matching, social categorizations might unfold as follows. Suppose that an inpatient portal shows the characteristics of a patient (e.g., gender, race, age bracket) who shared their experiences in a peer support system. As a consequence, the way an observing patient perceive a model's behavior is based on the model's observable intersecting identities (thus intersectional) and also based on the model's actions (thus dynamic).

Social categorization is intersectional because multiple identities (i.e., features) often overlap and create a unique "compound" identity. For example, pictures of Black men were rated more masculine, and therefore older; whereas Asian women were rated more feminine, and therefore younger [19]. Social categorization is also dynamic because some identities are more focal depending on the actions of the model. For example, a Chinese woman eating with a chopstick tends to be assigned with the "Chinese" category, whereas the same Chinese woman putting on lipstick tends to be assigned with the "woman" category [20].

The consequence of intersectional and dynamic social categorizations is that algorithmic peer matching will be incomplete if (1) intersecting features are not treated as a unified feature, and (2) the observer and the model's actions are not considered.

(b) The consequence of experience reduction arose when matching based on surface features (e.g., gender, race, or health status) failed to capture the complete experiences of the patients. For instance, some minority individuals can enjoy privileges from other sites (e.g., higher socioeconomic status). By simply matching using surface identities, such individuals may be matched with other marginalized patients simply because they shared similar surface features, rather than sharing common experiences of marginalization. Thus, Hanna et al. cautioned using race as a fixed attribute in algorithmic tools because such an approach minimizes the structural force that creates the marginalization experiences faced by racial minority individuals [15]. In short, surface-level matching may end up producing superficial and ineffective matches.

(c) The consequence of information exclusion arose when matching patients by their identities led to minority patients being connected only to other minority patients. Thus, while the patients might feel the matches are optimal, minority patients are excluded from the privileged patients. Indeed, supporting minority patients to connect could help them develop a collective identity around illness, which in turn, can spring into health advocacy at a collective scale [6]. However, the same tools can also hide unjust treatment often faced by minority patients because the algorithm excluded them from learning the experiences of privileged patients. For example, Black Americans often systematically received less pain treatment relative to White Americans due to racial biases among medical professionals [17]. Similarly, physicians are less likely to prescribe opioid medications to Black Americans [7, 27]. In short, inappropriate algorithmic matching and curation can hide unjust treatments in clinical settings.

With these three challenges and consequences, implementing algorithmic patient matching is non-trivial when facing the sociotechnical complexities of real-world scenarios. First, the way human sees identities is complex and more work is needed to understand how to capture such complexities in algorithmic systems. Second, superficial matching could match patients by their surface features rather than the similar experiences that they had because of their identities. Finally, unfair matchings could hide unjust clinical treatments experienced by minority patients. Speaking more broadly, algorithmic patient matching could unfairly hide patients' experiences that might be invaluable for minority patients to seek commonalities.

5 DISCUSSION

At this point, we reached a conundrum between using algorithmic patient matching to maximize the benefit of social modeling for hospital inpatients versus its challenges, including the consequences that could lead the algorithm to maintain injustice. In this last section, I will propose two recommendations on how to implement algorithmic patient matching.

(1) **Support patients' agency to develop a sense of similarity**. Given the complexity of social categorizations in informing social modeling as well as the potential adverse consequences of matching unfairness, I concur with prior work in Human-Centered AI that algorithmic patient matching tools for social modeling should augment existing human decision-making process rather than supplant the decision-making process entirely. Therefore, an inpatient portal with algorithmic matching systems should allow people to discover stories and learn about the storytellers' identities. At the same time, such a system can highlight patient stories that might be similar (and showing how it was determined as similar) while at the same time allowing patients to explore support content that matches their unique social categorizations.
(2) **Show critical identities as a starting point to identify injustice**. As I argued that it is best for patients to identify similarities, I also argue that showing critical identities (e.g., gender, race, age group, orientation) in tandem with deliberate cross matching (i.e., matching stories from models of different demographics) is necessary to help surface unjust clinical treatments. Furthermore, algorithmic tools can offer content from patients outside their group, thus reducing the tendencies to consume in-group content. By doing so, patients could be exposed to the experiences of minority patients as well as privileged patients. This approach can contribute to the ongoing work in countering injustices in healthcare.

6 CONCLUSION

In this paper, I highlighted the potential of using algorithmic tools to match patient stories (or experiences) with a goal to support patients' self-efficacy in managing their inpatient hospital experiences. Additionally, I discussed the three patient features for matching and the three challenges, especially in the complex nature of human social categorizations as well as how matchings can hide unjust clinical treatments. Finally, I offer two approaches to implement algorithmic patient matching and arbitrate the tensions between the opportunities, the complexities, and the potential unfairness of algorithmic patient matchings.

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