1. **Diabetes is at pandemic levels. Describe two areas of technology innovation on Diabetes Monitoring and Public Health Diabetes Efforts**

As diabetes has been widely studied, under the help of medical doctors and diabetes experts, it is now possible to implement wearable devices to track individual health information, such as blood sugar level and blood pressure. Using these information, program-based self-diagnosis systems can be used to perform real-time monitoring on the risk of diabetes of the device wearer, which can be reported to health care providers (Mookiah et al., 2013).

Beyond monitoring blood sugar level and blood pressure from individuals using wearable devices, the pandemic levels of diabetes can be also evaluated using data from social media. Karami et. al. implemented a multi-component semantic and linguistic framework, which was used to collect Twitter data, monitor and analyze the public opinion the relationship among diabetes, diet, exercise, and obesity (Karami, Dahl, Turner-McGrievy, Kharrazi, & Shaw Jr, 2018).

Furthermore, computational technology can help to improve the public health diabetes efforts. Currently, personalized Big data has been applied to Internet search engines (for example, for advertising purposes) (Couldry & Turow, 2014). Therefore, by "discovering and educating" diabetic patients, especially those with a history of unhealthy lifestyles, the search engine may suggest healthier alternatives when the diabetes-risk users are looking for specific consumption (such as ordering unhealthy food online).

1. **Explain what is novel and what will be required for these innovations to succeed.**

For the technology that we have discussed above, the innovations focus on applying ML algorithms and big data in a conventionally pure healthcare-related area. When these innovations are applied, it will require a balance between the trade0—off of model predictively and interpretability. The reason why machine learning algorithm is a powerful tool is that the ML provides high predict accuracy. However, ‘there is no free lunch’ (Xu, Caramanis, & Mannor, 2011): the improvement of machine learning accuracy is usually associated with sacrificing the model’s interpretability. ‘Black box’ algorithms such as SVM and neuron networks are powerful in predicting, but is hard for interpret on why the algorithms will make certain decision, which is what doctors really care. Thus, more simple-structured ML algorithms (such as decision tree and naïve Bayes) are more suitable for classification problems using public health information data, because these models facilitate clinicians and analysts to correlate model-predict results with their understandings and interpretation on real-word data (Kim, Cho, & Oh, 2017). For example, compared with the model accurately predict that a group of people will have a higher risk of diabetes, it would be preferable for clinicians and analysts to know why such kind of people are risky.

1. **How could this chronic illnesses be prevented on a pandemic level and what technologies could be used to do so?**

Unlike other chronic disease, ~95% of all the diabetes cases are Type II diabetes, which could be prevented by changing to a healthier life style or using medicine intervention. One way to prevent diabetes on a pandemic level is to apply computational technologies to screen the patient that develop diabetes risks on physician visits, and inform such information to their PCP, and potentially other healthcare provider. Sharing such information to the health providers could be helpful in patient educating, as patients tend to listen and follow the suggestions made by the PCP and nurse they are familiar with, rather than information from other information source (Haas, Leiser, Magill, & Sanyer, 2005).

When it comes to suggestions from health care provider, computational technology can also help patients to acquire their health care provider’s suggestions through telemedicine interviews. Telemedicine solutions allow patients to communicate with health care providers via internet devices, such as smartphones. If the patient is not capable due to reasons such as long travel distance, the patient is incapable to travel, or during infectious disease outbreaks, telemedicine can offer patients the interpretation on their concern related to diabetes or adopting healthier lifestyle from healthcare providers (Ayyagari et al., 2003; Dullet et al., 2017; Raad, 2010).

1. **Share and describe 5 solutions for prevention, monitoring, or treating Diabetes for either type**
   * 1. As we have discussed in Question 1, wearable devices can be used to monitor and prevent diabetes by tracking the wearer’s heath information such as blood sure and blood pressure.
     2. As we have discussed in Question 1, social media information can be used to monitor public opinion on diabetes.
     3. As we have discussed in Question 1, internet search engines can be used to monitor and prevent diabetes by suggesting healthier alternatives to diabetes-risky users.
     4. As we have discussed in Question 3, machine learning algorithm and big data can be used to monitor and prevent diabetes by informing PCP of the diabetes-risky users, encouraging them to make suggestions to their patients to prevent diabetes happening, or the development thereof.
     5. As we have discussed in Question 3, telemedicine interviews can be used to enable faster interaction between diabetes patients or potential diabetes patients with their healthcare providers, thus facilitate the prevention, monitoring, and treating of diabetes.

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