We are grateful that the paper was received well and that the reviewers believe our work makes a strong contribution. The AC and reviewers asked us to focus on specific areas to strengthen our paper; below we discuss how we intend to address the feedback into our camera-ready paper, if accepted, and are looking forward to doing so. We have thematically grouped the comments below -   
  
**Expanding the Discussion (AC, R1, R3)**  
The reviewers make a great observation that our discussion would provide a lot more value if we provide concrete examples of how our proposed ideas might play out in practice. We will add the following examples to the revised document.  
  
1. Theorizing algorithms - De Choudhury et al.’s [1] work in mental health is an excellent example, where the researchers validated constructs, focused on data biases and unobserved factors, as well as conducted sensitivity analysis. Moreover, they consulted domain experts for their feedback on ground truth labels.  
2. Engaging communities in algorithm design - Brown et al.’s [2] work depicts how communities can help unravel critical perceptions of algorithms and their use. PD can help identify and incorporate these interpretations earlier in the design process.   
3. Limitations of Participatory Design – R1 makes an excellent point that PD has its limitations, and we appreciate the relevant references to PD in public services. We will incorporate these papers into the discussion of the revised document as an example of how PD can be conducted in public services within institutional constraints. PD still has a pertinent role to play in that the stakeholders could help label data for ground truth, give input on salient features, evaluate the quality of classifications, etc.  
4. Our recommendations – We go beyond Baumer’s framework and offer unique recommendations such as using predictors had have been hard to quantify thus far (for e.g., case notes) and focus on outcomes that disrupt the status-quo and improve children’s lives. We will clarify them further in the revised document.  
  
**Tensions between theory-driven and human-centered (AC, R1)** – R1 rightly notes that theory and human-centered approaches may conflict and will need to be reconciled in order to move the field forward. A lot of the theoretical knowledge in child welfare literature has been curated through qualitative studies (followed by validation studies). In this regard, much of the theoretical knowledge in CWS is human-centered and applied. However, the policy and systemic barriers make it hard to even explore some well-studied theoretical approaches. This interaction between policy, practice and algorithms is an open discussion, and we will highlight this tension between street-level work and algorithm design in the revised document.  
  
**Make technical concepts more accessible to non-experts (AC, R1)** – Thank you for raising this very valid concern. We will further clarify in the revised document how GLMs and machine learning methods (supervised and unsupervised) differ from one another. We also provided a social interpretation of algorithms through the lens of Street-level algorithms [3] to elucidate that the algorithms that we are focusing on are the ones that are used to make on-the-ground decisions about human lives and welfare. That is, algorithms that directly affect families involved with CWS and not second or third-removed algorithms that might be internally used by CWS or government analytics teams.  
  
**Proposed Systems (AC, R3)** – We analyzed the proposed systems to better assess what solutions are being proposed and whether they address some of the ongoing problems that affect child welfare practice. Most of the proposed systems only employ newer computational technologies such as neural networks, CART algorithm, Bayesian networks to improve the predictive accuracy of the models without actually addressing concerns around data integrity or their ‘deficit-based’ nature. In Recommendations for Future Research, we discuss that recent studies continue to focus on risk assessment and uncritically reproduce the status-quo (deficit-based framing). Moreover, these systems are not being deployed in practice because of a lack of transparency offered by neural networks and several ML algorithms (see Results subsection Machine Learning (ML) approaches). We discuss proposed systems that offer merit and sought to solve a problem instead of simply using a newer computational method and focusing on improving predictive accuracy. For instance, we discuss the importance of proposed cumulative risk models and causal models in the Discussion section. We also discuss the child-foster parent matching model that breaks the status-quo and seek to improve the lives of foster children.  
  
**Emphasis on US-based projects (AC, R2)** - We will add a limitation that our work is focused on the U.S. child welfare system. Most of the novel algorithmic work in child welfare has been pioneered by the Children’s Research Center (CRC), which is based in the United States. Recent government proposals to push for data-driven decisions in CWS have also made it necessary to analyze U.S. based systems [4]. Moreover, as researchers working in the U.S., we have access to and a better understanding of the U.S. based child welfare system.  
  
References  
1. De Choudhury M, Kiciman E. 2018. Integrating Artificial and Human Intelligence in Complex, Sensitive Problem Domains: Experiences from Mental Health. AI Magazine.  
2. Brown A, Chouldechova A. 2019. Toward Algorithmic Accountability in Public Services: A Qualitative Study of Affected Community Perspectives on Algorithmic Decision-making in Child Welfare Services. CHI 2019.  
3. Alkhatib A, Bernstein M. 2019. Street-Level Algorithms: A Theory at the Gaps Between Policy and Decisions. CHI 2019.  
4. Using Data To Help Protect Children and Families Act. 2018. 115th Congress, Senate of the United States.