



The Absence of Data Visualisation in Midwifery

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March 18, 2021

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Abstract— Information visualisation creates visual representations that more easily convey meaningful patterns and trends hidden within large and otherwise abstract datasets. Despite potential benefits for understanding and communicating health data, information visualisation in medicine is underdeveloped. This is especially true in midwifery, where no qualitative research exists regarding the impact of different graphs on clinicians' and patients' understanding. This *position paper* is part of ongoing work investigating this gap and its potential impact. This work reviews a collection of literature from within the midwifery domain. We found almost two-thirds do not use data visualisation approaches to present knowledge realised from data, and those that did were generally restricted to basic bar charts and line graphs. Without effective information visualisation midwives will continue to be constrained by the challenge of trying to see what datasets.

Keywords— data visualisation, information visualisation, midwifery

I. INTRODUCTION

Midwives generally work with well women and their babies, promoting and guarding normal birth and enabling informed consent and health education for women and their families [1]. While provision of direct patient care will continue to be the driving concern of midwifery, how midwives engage with patient data and research will evolve in the era of big data [2, 3]. Many consider data science the next evolution for midwifery, yet the literature shows that few actually understand what this means and the impact it may have [2-4]. Ubiquity of electronic health records (EHR) has changed the way we collect patient data, and as the domain of learning health systems (LHS) continues to evolve and receive greater attention from clinicians, it is possible for midwives to see that large collections of EHR can be the source of powerful and precise knowledge about medical diagnoses, treatments, and likely outcomes for individual patients [5, 6]. Midwives must first be able to understand current data and findings for themselves before being able to present information to pregnant women and their families in an accessible way that ensures understanding for the layperson. In this paper we show that data visualisation is especially underdeveloped in midwifery and we investigate the potential consequences of this problem.

II. THE CASE FOR DATA VISUALISATION

Increasingly, it is recognised that effective information visualisation may hold the key to unlocking access to

understanding the complex data in EHR and LHS. Information visualisation is the study of transforming data, information and knowledge into visual representations that can more easily convey meaningful patterns and trends hidden within large and otherwise abstract datasets [7-9]. A 2011 report by the US Institute of Medicine (IoM) described information visualisation in clinical medicine as underdeveloped when compared and contrasted with other scientific disciplines [10].

Finding an appropriate and comprehensible form to visualise and communicate data with the public is a challenging task [11]. Several studies have investigated the effect of graphs in patients' and clinicians' understanding of medical risks [12-14]. The results are mixed and definitive recommendations cannot be easily made. Finding the most appropriate way to visualise data and communicate their messages depends on the presenters' objective, the communication context and the targeted audience [13, 15]. Users' likes and dislikes should be taken into consideration, but must not be treated as the gold standard [11]. For instance, users seem to prefer graphs that are simpler, but simple graphs are not always able to convey complex information which can lead to a misunderstanding [16]. [17] found that doctors performed worst with the format they liked best, and best with the one they strongly disliked.

Absence of or ineffective data visualisation has negative effects on clinical care, time efficiency and patient safety [18]. Those viewing raw or ineffectively presented data get lost, especially where they have to take data from one variable and relate it to data from another variable in order to arrive at meaningful information for use in immediate clinical decision-making [18, 19]. Effective data visualisation can mitigate the issues that arise when deep insight is required to analyse data and make time-sensitive decisions [19]. Providing visualisations for data supports users and mitigates the complex issues of comprehension, interpretability and navigation as they traverse large collections of information [20, 21]. Many studies into the benefits of data visualisation have been reported in non-clinical domains. Surveys within those domains confirm that professionals do recognise the

IoM contends for medicine, that they may be valid across the entire body of the literature. This can only be established with further investigation.

A limitation of this study is that it only sourced papers in the midwifery domain that specifically used the term data visualisation. Future work should include; (i) review of a broader collection of midwifery papers, for example, the entire collection of midwifery papers published in a given month or year, to ascertain the distribution and scope of data visualisation for the domain, (ii) an assessment of the impact of different visualisation formats on midwives' clinicians' and patients' data understanding.

V. CONCLUSION

Data visualisation is necessary to complete understanding and contextualisation research and evidence. This *position paper* has presented formative work investigating the use of data visualisation within the domain of midwifery. The consequences of poor data visualisation can impact midwives' understanding of data and current research, and limits their ability to present information to colleagues and patients in an approachable form. Research is needed to assist midwives who work with or publish research using data to identify and present data in a focused issue- and audience-relevant manner. Without this, midwives will continue to be constrained by the challenge of trying to see what datasets hide.

ACKNOWLEDGMENT

BJD, SM, EK, GAH, and NF acknowledge support from the EPSRC under project EP/P009964/1: PAMBAYESIAN: Patient Managed decision-support using Bayes Networks.

COMPETING INTERESTS

No author identified a competing interest relevant to this research.

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