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# Aesthetically-Enhanced Visual Analytics Platform to Explore Patient Metadata

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**The domains of Human Computer Interaction and Visualisation are arguably two separate but related disciplines. Both domains often focus on providing intuitive interactions and look to provide optimal cognitive ergonomics to facilitate task completion and/or ease of use. In this position paper, we discuss how combining these disciplines can be critical to the field of Visual Analytics. The paper further eludes to a Visual Analytics platform being developed to help researchers explore patient metadata to facilitate comprehension of a patient population.**

*Data, visualisation, visual analytics, human computer interaction, cognitive psychology*

## 1. INTRODUCTION

Human Computer Interaction (HCI) and the domain of Visualisation are two separate, but increasingly interlinked disciplines [1]. The purpose of visualisation is to aid the understanding of complex data. Typically, visualisation focuses on static displays of geometric shapes created to represent data [1]. These shapes are then commonly optimised to garner further information from often complex datasets. Conversely, HCI focuses on interactions encountered between users and a digital system [1]. Its purpose is often to help facilitate the user in completing a task, or series of tasks. Consequently, these two domains are often combined and referred to as “Visual Analytics” [1], which involves enriching visualisations by adding dynamic, and often interactive methods aiming to facilitate the comprehension of complex data. Thomas & Cook defined visual analytics as “the science of analytical reasoning facilitated by visual interactive interfaces” [2]. Motivation for research focus in this field derives from the need to better understand data which is becoming much larger in scale and increasingly, in dimensionality [2]. Therein, interactive visualisations can facilitate the visual exploration of data using novel, creative and experimental methods to better understand a dataset. This exploration could further facilitate the data being viewed within a panoramic perspective, enabling users to discern comparative information from data.

Visual analytics with HCI typically encompasses pixel based actions on GUI elements (e.g. buttons, sliders, dialogs, status bars/symbols etc.) [3]. To achieve this, a cognitive association is required to transverse the bridge between physical/cognitive action, artificial objects (GUI elements), and the perception of geometric shapes created to represent data [3].

Success obtained from visual analytics can be two-fold; 1) the functional ability of its users, i.e. it is vitally important to implement appropriate HCI techniques into the development cycle, and 2) it is dependent on user understanding. It is essential to support cognition using defined HCI techniques (such as visual hierarchy) [4]. Furthermore, it is equally important to determine the goal(s) of the user to enable effective information structure and visualisations to be generated [5]. These techniques are often also represented in the form


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of infographics, which make complex information accessible for the lay reader.

Traditionally, visualisation methods tend to focus on the most efficient and effective methods to represent data (i.e. without unnecessary information) [4]. However, interestingly, within the domain of interaction design, it is often recognised that "aesthetics is an integral part of functionality, with pleasure a criterion for design equal to efficiency or usability" [6]. With this acknowledgement in mind, the domain of visual analytics can therefore facilitate exploratory research motivated by curiosity and reflection [7]. This may lead to data being represented in a more unconventional manner using novel interactive data visualisation techniques and animations. This facilitation could thereafter encourage and assist users in 'smarter', more inquisitive data investigation rather than solving a predefined series of questions [7].

Consequently, visual analytics design is becoming an increasingly important area of HCI research. As design is a multidisciplinary craft often requiring an intricate knowledge in both; 1) design theory and practice, including; principles to be employed, experience with design applications, and appropriate design expertise for a project, 2) a working knowledge of the project domain and users, this will often include; cognitive engineering (i.e. user experience management), software engineering awareness, and a study of contextual ethnography [8]. With this in mind, 'design' is a team exercise which should include expertise capture from all key stakeholders.

Furthermore, as data banks and repositories are becoming larger and increasingly more complex, the field of visual analytics is challenged to create progressively sophisticated, yet usable data visualisation interfaces [9].

As data analysis has conventionally been performed within the context of scientific research, typically by an academic or data scientist, the aesthetics of data visualisation have often been neglected in favour of the optimisation of complex data analysis techniques [9]. Nevertheless, user experience experts such as Don Norman famously stated how "attractive things work better" [10] and how "advances in our understanding of emotion… have implications for the science of design" [10]. Employing this hypothesis to the domain of visual analytics we can aim to exploit future iterations of data visualisation by encouraging an emotional response to task-based objectives. Norman elegantly illustrates this effect in this brief anecdote:

*"In the early days of the personal computer, all the display screens were black and white. When color screens were first introduced, I did not understand their popularity. In those days, color was primarily used either to highlight text or to add superfluous screen decoration. From a cognitive point of view, color added no value that could not be provided with the appropriate use of shading. But despite the fact that the interface community could find no scientific benefit, businesses insisted on buying color monitors. Obviously, colour was fulfilling some need, but one we could not measure. In order to understand this phenomenon, I borrowed a color display to use with my computer. After the allocated time, I was convinced that my assessment had been correct -- color added no discernible value for everyday work. However, I refused to give up the colour display. Although my reasoning told me that colour was unimportant, my emotional reaction told me otherwise"* [10].

In this scenario, although Norman was unaware of his 'need' for a colour monitor, 'color' itself became a decisive factor in his future personal computer requirements. This indicates a more nuanced aesthetic affect encountered by the user. This effect can be harnessed, experimented with, and assessed, as the affective system is often deemed 'judgemental' [10]. Therefore, by creating a visual analytics system which displays data efficiently and effectively, as well as having a contextual aesthetic appeal whilst engaging with a user in an effective interactive manner, we can create an optimum system for data exploration and analysis.

Furthermore, as software development, UI design and UX engineering are becoming increasingly accessible/available to lay audiences, the ability for data visualisation across various domains becomes achievable [9, 11].

Publicly available data is commonly classified as 'open' [9]. Nevertheless, this does not signify data comprehension is obtainable. Therein, typically one must be a data scientist to explore and analyse open data. However, visual analytics systems, could truly facilitate data 'openness', thereby facilitating true data comprehension by the general public.

At its core, Clinisent is a reporting platform which facilitates the transfer of data between clinical laboratories, patients and practitioners. With collaboration between Clinisent and Ulster University, an interactive visual analytics dashboard has been created to represent a patient record dataset. The aim of this research is to create a platform which enables the exploration and comprehension of this, often complex, patient data. Initial phases of development will focus on metadata exploration by employing novel, dynamic and interactive visualisation techniques.

## 2. MODEL DESIGN

A series of functional requirements have been gathered, wireframes generated. User experience wireframes were then discussed, refined and presented for review. On review, a final user experience design was confirmed and an initial user interface design was developed. Through an iterative refinement process a final UI was selected.

A minimal viable product (MVP) developed. An evolutionary prototyping model was followed enabling continuous refinement. This MVP provides a clickable demonstration of how both researchers and lay audiences can dynamically interact with a dataset via web based inputs to generate metadata visualisations.

A decision tree mechanism has been implemented to facilitate datatype selection a user wishes to understand, compare or contrast. To facilitate the data aggregation from a specific cohort demographic filtering is attained via novel HTML5 web form inputs. The current iteration of metadata visualisation includes: a spatial representation of record collection location, a linear representation of when records were collected, part-to-whole representation comparing datatypes selected, and population pyramids conveying age/sex categorisation.

The platform has been developed to be device agnostic and system independent, therein accessible via a device with an internet connection and access to a web browser. The platform was developed using HTML5 for webpage structure, CSS3 for webpage formatting, JavaScript for dynamic interactivity, and D3.js for geometric data representation.

To create a platform such as this a number of considerations must be made. Firstly, as the platform aims to utilise patient data, a primary consideration is the responsibility to ensure data security. Secondly, to attain access to patient records we must employ patient specific consent models to facilitate individual users the ability to share/donate their data for research purposes. Thereafter, patients must also be provided with visibility on how their data is being used and any outcome of the research. All data collected, processed or presented must also adhere to up-to-date and relevant data protection legislation, including European General Data Protection Regulation (GDPR).

Further, evaluation of this platform will be forthcoming by placing this prototype in the hands of external customers in which direct requirements and specifications will be attained. Implementations can be seen in Figures 1 and 2.


***Figure 1:*** *A visual representation of the visual analytics dashboard MVP*


***Figure 2:*** *A portion of the visual analytics dashboard illustrating the collection location of patient records which are currently available, number of records available, gender and age breakdown and timeline of record capture*

## 3. CONCLUSION

As data repositories become increasingly important, useful and valuable, it is inevitable data storage will become bigger and more complex. Accepting this, it is vital to provide avenues of accessibility to exploit available data. Therefore, in future, a deeper integration of HCI and data visualisation methods is to be expected. Furthermore, the advance of data mining, machine learning and artificial intelligence are likely to become key features in enhancing visual analytics services. As a result, this project aims to create an accessible, interactive visual analytics platform to facilitate the exploration of patient data. As McCormick et al. states "Visualization offers a method for seeing the unseen. It enriches the process of scientific discovery and fosters profound and unexpected insights. In many fields it is already revolutionizing the way scientists do science" [12].

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