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DATA AND PRODUCT DEVELOPMENT: THE NEED FOR A DATA PRACTICE PARADIGM IN DESIGN EDUCATION, A PROJECT-BASED REFLECTION ON USING MATLAB SOFTWARE FOR SENSOR DATA CAPTURE AND ANALYSIS

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ABSTRACT
This paper discusses how MATLAB software was integrated into the research and design process by capturing and visualising data to inform a 4th-year capstone undergraduate industrial design product development project. Examined within the project framework are perspectives on; data use for design projects from the literature, data collection, understanding project data, designer alternate skill set, using data to justify design direction, associated data capture technologies, data-driven changes of state for UIs (User Interface) and a proposal that designers need to have a data practice paradigm. As technology rapidly embeds into almost every aspect of society data is produced and captured at a diversity and scale previously unparalleled. Tools and systems to capture and assess such data simultaneously are being democratised, bringing new understandings and accessibility to systems for testing hypotheses more efficiently, either with sensor-based open-source hardware microprocessors or commercial data capturing systems. Designers developing smart products, smart system proposals, and IoT devices need to integrate these data capture and assessment tools into traditional product development and research processes. This is especially significant in projects where subtle technical innovation and application of new technologies, “technology epiphanies”[9], or natural user interfaces (NUI) are present. These themes are critical to designers at present; engineers, data scientists and computing scientists apply data analysis techniques to design problems previously in the product designer’s training skillset. Having an applied understanding of such processes would permit designers to regain control over domains slipping into the grasp of allied product development disciplines.

Keywords: Data, MATLAB, Simulink, user interface, UI, TUI, NUI, IoT product development, control systems, Arduino

1 INTRODUCTION
As products become more connected and digital, and as machine learning creates new interactions to collected data, designers need to understand how this data is appropriately collected and utilised and how this can augment their conceptual thinking around solutions. A discipline specific data practice paradigm for undergraduate students needs to be developed around quantitative data; currently the waters are murky for product design concerning data practices. We can learn pre-existing processes from our colleagues in the computing and hard sciences. However, a defined flexible model suitable for design is needed, a carbon copy is inappropriate. Qualitative research methods taught in undergraduate programs suit many design problems and practices but not all. The diversity of projects and evolving practices in the industry around quantitative data needs attention. For example, final year undergraduate product design major research projects take many forms, from highly conceptual to incremental innovation, highly technical to low technical, form-driven to function-driven, research-driven to development-driven, market-ready to crude conceptual mock-up, degree programs assessing an equal balance or varying degrees of each distinction. Nuances between product and industrial design programs and school to school, guide where the focus may be. All programs, however, strive to get a well-balanced demonstration of prior learning in a focused project. What is needed to meet future challenges of designing products is working with quantitative data, "With data and machine intelligence being the

design material of the future..", [13]. Some experience using data on at least one part of a major design project is essential for young designers, no matter the type of project. For example, collecting Tall-Data or Fat-Data, rather than qualitative Thick-data on an existing product's performance may help young designers conceptualise how their product may function better, or be augmented with real-time machine learning, thereby enriching design concepts beyond non-smart products.

2 DATA USE IN DESIGN TO REDUCE ASSUMPTIONS

Reducing subjective assumptions from the product design process, especially at the front end of a project, allows deeper reflection of functionality or feature design in the backend. As discussed above by Hou, Liang & Jiao, data can be accumulated at multiple points in the lifecycle of a product as well as multiple points in the product development phases. Professional designers, let alone undergraduate students completing major product design projects, cannot verify all aspects of their design decisions with data or even literature research. Ideally, data-guided research should be used for at least one of the product development activities in the product development cycle.

2.1 Product feedback loop

The UX interaction community and TUI discipline use a data-driven feedback loop [13]. This data-driven feedback loop drives concept testing and adaptation. There are highly polished UX research project process examples, however these examples tend to have a simple design aesthetic and focus on interaction rather than the well-designed physical object. They spend more time prototyping the interaction and creating a feedback loop, whereas product designers focus on the object and simulate how the product will be used or interacted with. Combining both methods, a polished visual design and a polished interaction are ideal. One sees a push to necessitate this data-driven-feedback loop within product design schools. However, as discussed above, this is logistically difficult due to the scale of undergraduate product design projects. There is tension and competition between UX computing and design disciplines, computing scientists relying on data to design and designers relying more on experienced-based intuition. Historically, designers are focused on non-smart products, lifeless non-digital products that are continuously commoditised to the point of disinterest to the public view, and therefore a shrinking new product development area. The generally more interesting design projects blend the two methods. It could be argued that a designer with data capture and development skills using data-guided intuition, not just 'intuition'[2], would be better placed to develop projects with greater projected vision. In product design, where the problem or requirements are not necessarily apparent, or "the client's brief will be vague, it is only by the designer suggesting possible solutions that the client's requirements and criteria become clear." [2]. Moving into the future, student product designers with experience using quantitative data somewhere in the 'data loop' will gain deeper insights into product development previously inaccessible or, from a practical perspective too challenging to complete.

2.2 Data capture practices vary across disciplines

Design problems and projects are varied and so, too, are the types of data required to considerately propose an effective solution. Where a student project starts, either at the defining of the problem phase or after the problem has been clearly defined, this influences the approach to a project and, therefore, what type of data is to be collected or assessed in the investigation or validation phases. Many factors influence the design process research strategy and therefore data collection methods, however, clear research paths have been established in the sciences with a long history of the scientific method defined. From the onset, students receive a clearly defined investigation, with clearly defined research processes, and therefore have a ‘hit the ground running’ approach to data capture and evaluation. Design projects are different, problem-identification and problem-solving approaches are diverse. The value of a designer is not in the pre-set design project with pre-set methods and a closed brief. Design thinking training is about approaching problems without a pre-set strategy. The ‘wicked problems’ and the ill-defined is where designers’ skills are valued, pre-setting all aspects of a design project reduces the student training in defining a project with ‘appropriate to the project methods’, whatever they may end up being. As discussed by Pavliviscak in 2015, "There is a lot of hype about data-driven or data-informed design, but there is very little agreement about what it really means"[11], 'Big-data' defines large data sets, 'thick-data' ethnographic interviews and surveys. Big data is further apportioned into; "Tall Data where the number of observations is large, and Fat Data where the number of variables is large”[7]. Scientific engineering data approaches to problem-solving tend to be "theory-based models, these encapsulate cause-effect relationships between variables that have either been empirically proven or theoretically deduced from first principles."[6]. Essentially data is collected between small changes in variables within designed experiments, a 'Black Box' approach to deduce performance. This "engineering design process generally encompasses; the requirement analysis, conceptual design, embodiment design, and detailed design phases, which is enacted through a cascading mapping of design decisions regarding customer needs, functional requirements, product architecture, and the end-product specifications". [14] Big data is often collected without a goal or experiment in mind, [6] and analysed to identify insights or patterns. Blended or hybrid approaches such as "Theory-Guided Data Science"[6] and 'big-thick blending', as Bornakke & Due discuss in their 2018 article, *Methodologies in how to approach blending data sets,* suggests the requirement of data analysis expertise across data analysis disciplines. Bornakke & Due conclude their article by stating, "Blending thus joins with the growing choir of digital-based scholars who suggest that social scientists abandon the historical ideal of the renaissance person, bound to the individual but genius scholar who masters all methods" [1]. This statement was made without even including engineering theory-based data collection methods. This highlights the challenge of data collection for design projects, and what data collection and analysis methods should be used for design projects, or, more importantly, what methods we utilise when training and testing our undergraduate designers. This highly multifaceted methodological decision needs some form of resolution if product design degrees are to stay competitive or relevant as HCI computing graduates take on traditionally held product design ground. Adding; quantitative data capture, data analysis or data responsive design to at least one phase of the design process in undergraduate product design courses would help designers stay relevant. One trialled approach, to be discussed below, is the capturing of scientific engineering variable data, which, for undergraduate projects, may prove appropriate. Using a loose engineering method, it was possible to identify variance in the data, this guided project parameters and added a level of quantum to the project. Moreover, like many student design projects, completing all aspects of a design project, essentially producing market-ready products, is unrealistic due to time, money and infrastructure. However, like the theoretical building blocks of scientific knowledge, the 'yes I think this is feasible' building blocks of a product design project can be fortified with data, thus improving design project justification whilst at the same time preparing undergraduate students to gain rather than lose ground to allied disciplines in the competitive world of new product development.

2.3 Student project overview

This trialled student project uses a 4th-year Undergraduate Industrial Design project as the lens to examine an approach to data use for new product development. The project focus considered "How can electronic integration read terrain and provide a reliable geometry adjustment system for mountain bikes?" This project question was deduced after the initial research and market gap identification around mountain bike geometry affecting stability and performance. The sport of mountain biking is very popular, with several sub-disciplines coming under the mountain biking category, each with particular preferences for specific frame geometries. Bike dynamics and geometry are quite complex. [5] Recent work has been done to explain stability and bicycle control, computational models have been developed to support dynamics assessment. However "The relationship between design and behaviour is shown to be heavily speed-dependent and complex" [12]. Vehicle dynamics define non-subjective aspects such as stability and dynamics, how a bicycle feels to the rider is "subjective opinion"[8]. There are some 'knowns' such as; changing the head angle increases or decreases stability and responsiveness at different speeds depending on the angle, a short chain stay provides a more dynamic ride in the back end of the bicycle. These aspects are explained in the literature along with a number of other relationships. With a bicycle, even small changes in the basic variables such as bicycle geometry, rider height, weight, skill, and varied course routes that include slow, fast, inclines and declines all influence the feeling of stability. Therefore, there are many variables making mountain bicycle performance challenging to evaluate. The student identified that a dynamic, responsive system to adjust the geometry to increase bicycle handling characteristics based on speed and incline would make sense to develop. The system would adjust on the fly to suit stability vs power geometry depending on conditions and rider preference needs. A product design approach rather than an engineering approach is needed to produce a product concept within the timeframe of an undergraduate project due to the above discussed variables. However, if the engineering data collection methods were used more loosely, valuable data could be collected to guide the design project.

2.4 Data collection and data processing for visualisation and real-world workflow

Keeping student projects simple enough to execute, and at the same time with enough research training, it was decided that collecting quantitative data that verified bicycle geometry stability through MOU sensors rather than opinion would be the approach. MOU sensors come in several forms, from high-calibrated research equipment to inexpensive Arduino board MOU add-ons. Capturing quality data accurately required at least four considerations; repeatability, accuracy of test equipment, test rig design, data processing and visualisation. Immediately there is a test complexity that is a yearlong project in itself. This was a design project, not an engineering project. There was no test lab and no high-end test equipment available. Research equipment commonly comes with proprietary software to aid in data capture and visualisation; accessing this was not an option for this project. The data collection approach was formulated through how the data could be visualised using software, visualisations being the preferred language of designers, so this was the main criteria for selection. Python, R and MatLab are commonly used in teaching environments to visualise data, Matlab more specifically is used in engineering and data analysis[10]. Matlab, "Rather than relying on some foundational knowledge of coding or computer science policies, MatLab instead allows users to get a more intuitive read on their data"[10]. This coupled with; accessible proprietary software training, integrated smartphone accelerometer and GPS data capture software and Simulink, Matlabs integrated ecosystem of products lent the selection towards Matlab. Visualising data is one thing, utilising this for machine control or machine learning is another. Simulink would support an experimental workflow for this development in a real-world application, therefore supporting the appropriateness of MatLab is a tool for this application. As discussed, design projects and design problem-solving methods vary, there is no discipline-specific data practise paradigm for product design or industrial design, therefore, due to product development practice links with engineering disciplines, MatLab was trialled. It was also decided that the Matlab ecosystem could support an array of design projects from big data sets, often used to identify issues relating to 'wicked' problems, through to engineering data analysis and machine control.

2.5 Data capture approach

What does mountain bike stability look like in data? This was the first student project question needing to be answered. Question two was to confirm if this was measurable. It was decided that stability for the project would be assessed through an absolute frame and handlebar direction field testing experiment and if a higher variance was found, this indicated less stability. There are other ways of assessing stability, however these were discounted to reduce the number of variations in the experiment.

2.6 Student project outline

Developing a faultless experiment in the context of a design project in an undergraduate product design degree in all but the most straightforward projects would be unrealistic as discussed above. However, in setting methods and parameters for this experiment, reducing variables and increasing repeatability with resources accessible was the goal. Quantifiable in-the-field testing results for stability are not freely or identifiably available for mountain bikes in the literature; this may be due to the mountain biking industry's infancy, or a desire to keep proprietary knowledge secret. Either way, data was not available and needed to be captured by means accessible by the student. A broad overview of the data capture experiment will be covered below for context and is not an exhaustible discussion of the experiment.

<u>Aim</u> - To run an experiment to quantifiably classify a difference between two mountain bike geometries. Expert sponsored team riders identify a difference between lively and slack/stable geometry mountain bike setups in the industry, however these are based on professional opinion, not quantifiable data. The project aimed to collect quantifiable variance data.

<u>Hypothesis</u> - That it is possible to identify variance and classify variance between the absolute frame and handlebar direction of two mountain bike geometries in a real-world environment by logging azimuth, pitch, roll and MALMS to identify lively and slack geometry.

<u>Methods</u>

Equipment - To assess stability, a rig was required, this included; two smartphones running Matlab Mobile, the MathWorks data logging app, a mountain bike with a two setting manual geometry adjustment system, and stable phone mountings to secure the two smartphones.

Environment - A 140-meter section of test track was identified for the 'in the field' data capture. This included cross country inclines, declines and corners, hypothetically some sections favouring ‘slack/stable’ geometry and other sections favouring ‘lively’ geometry.

Process – To reduce variability in time to complete the course, trail runs were carried out until there was consistency in rider performance. Next, data logging test runs were completed, the most consistent time-based logs were used to compare the two different mountain bike geometries for stability comparison. Using smartphones running Matlab mobile; azimuth, pitch, roll, MALMS and GPS coordinates were logged along the 140-meter track. This data was logged, then graphed using Matlab and viewed as overlapping events, the most consistent time events were used. In the graphs a variation could be identified. GPS coordinates of the event were mapped alongside the graphs helping visualise event occurrences in the graphs.

<u>Results</u>

A classifiable difference between the mountain bike geometries was extrapolated from the data, supporting the hypothesis that variance between the absolute frame and handlebar direction is an identifier of stability. This result is consistent with professional rider opinion. Interestingly, the student test rider identified points where stability was felt however this did not necessarily reflect in the data. Another data point may be required to capture the whole rider experience completely. However, the already captured data is arguably all that is needed for the machine learning system design to operate effectively.

2.7 ‘In the field’ experiments

'In the field' experiments are challenging to set up and are open to a wide variety of variabilities and interpretations. This may prove too challenging in some instances for scientific professions to engage in, the degree of difficulty for replicability of data quality in experimentation may reduce their commitment to ‘in the field experiments’. Designers are more comfortable with making mistakes or finding variance in results. This may be an advantage for the design professions in new product development industries and, conversely, less successful for incremental innovation where the scientific process of variable reduction is possible. Designers use intuition more frequently to move projects forward quickly. This may also be true for the intuition of the data capture and the interpretation process. Some supporting data, not definitive data, maybe is all a designer needs to move a project forward. The success of new product development in consumer item categories does not necessarily rely on data, but on intuition, using a variety of inputs, including some data, may improve outcomes. For example, we have seen many heavily data-driven new products fail in the marketplace; think of Google Glass as an example. One way forward may be to encompass using data, but not relying on data. A designer data intuition product development process may serve as an appropriate method in new product development.

3 WHY IS A DISCIPLINE-SPECIFIC DATA PRACTISE PARADIGM IMPORTANT?

Understanding the way quantifiable data is; captured, cleaned for use, what patterns are discoverable, all provides a valuable framework with which to work. Designers can use data as hard and fast facts, inspiration, or a building block for intuition. Data can also be used as a design medium to augment or adapt experience through machine learning adaptations using Matlab Simulink. Identifying what a version of ‘stability’ looked like was a starting point for identifying and accessing what data is needed for machine control solutions. Some data handling programs integrate with machine control software, so it is possible to realistically develop and experiment with machine learning to solve design problems. Simulink, the Matlab add-on, is a primary example of this integrated system. Further to this, identifying 'stability' in the data, inspired a discussion around; if we can identify stability through data, and we can identify which geometry is better for the different conditions based on data, then we can create not only a device that changes according to the physical condition, but it is possible to consider an interface that adapts over time using machine learning. We can then also discuss interfaces that communicate more than basic condition settings of setting 1 or 2. Discussions around what the product should look like, what the UI is for this type of product. Is it a UX interface, or a TUI interface, is it a combination of both? New product development is currently grappling with these issues, especially in the health and fitness realm. Collecting data, looking at what data might infer, then thinking about how to integrate this data usefully into a product is a valuable discussion to have with undergraduate students. Therefore, we need to develop a discipline specific data practise paradigm for product design to prepare our undergraduate students better.

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