A systematic literature review on utilisation of behavioural data in service design: Unexplored potentials on data utilisation on co-design

Mika Yasuoka[1], Yuki Taoka[2], Momoko Nakatani[2], Nana Hamaguchi[3] and Shigeki Saito[2]
mikaj@ruc.dk
[1]Roskilde University, Denmark
[2]Tokyo Institute of Technology, Japan
[3]NTT Social Informatics Laboratories, Japan

Abstract

This study provides a systematic literature review, investigating current uses and application of behavioural data in services design process. The results show a predominance of data usage either on product design process by professional designers or on personal reflection by service users, and more importantly, there is a large gap in what designers and users can benefit from data. The paper argues that such a gap limits the potentials of data in service design and highlights the importance of co-design between designers and users within data-driven design.

Keywords: behavioural data, data-driven design, co-design, sensors and IoT

Introduction

Recent advancements in information and communication technologies (ICT) such as IoT and wearable devices have made it possible for us to easily acquire vast amounts of behavioural data. Behavioural data is defined as “a collection of specific information, referring to data from sensors, self-logging, telemetry, or social networks which capture people’s behaviours and patterns” (Ortega, 2022), and now used to conceptualise, develop, and maintain services and products, as Data Driven Design (DDD) (Kirk, 2016). DDD has attracted more attention in the field of design research ever before, which is evident in increased numbers of review articles (Bertoni, 2020; Montecchi and Becattini, 2020) and thematic articles of design journals (Kim et al., 2017). Studies on utilization of quantitative behavioural data in design are currently in their infancy and are expected to grow exponentially over the next few decades (Kim et al., 2017; Montecchi and Becattini, 2020).

DDD research topics include DDD framework (Trauer et al.2020), values on quantitative data for design (Montecchi and Becattini, 2020), impacts of DDD on expert designers and design teams (Bertoni 2020, Cantamessa, 2020), decision support for experts (King 2017), and case studies of behavioural data utilization in product design (Trauer2020). DDD research has spread to diverse topics related to behavioural data utilization in design.

On the other hand, comprehensive service design research on utilization of behavioural data obtained from IoT and wearables is limited. For example, Bertoni (Bertoni 2020) conducted a survey of service design literatures on data source and algorithms processed in analysing data but have hardly touched upon its wearable data itself or its potentials for service design domain. Bertoni (Bertoni 2020) pointed out, majority of existing studies used social media and online reviews as data sources and derived user needs through text mining, while direct user behavioural data such as sensing and wearable data have been hardly explored.

Regarding behavioural data from sensing and wearable, we have only limited knowledge about its usage on services design. First, considering "who" is using such data, the research identifies not only designers but also ordinary users who use the service (van Dijck, 2014) are data users. Since user participation and involvement in the design process are becoming one of the mainstream agendas in the field of service design, it is possible and ideal that users will and can use own behavioural data in design process. The service design research community has also hardly known how behavioural data has used in co-design. In addition, knowledge about behaviour data processes is limited. While quite a few research investigated algorithmic perspectives on data processing, it has not been clear how behavioural data on sensors and wearables are collected, processed, visualized, and used for design.

To sum, there are two major questions regarding behavioural data in the service design domain. The first question is about users or viewers of behavioural data acquired from IoT and wearable sensors. In other words, it is a question whether data consumers are limited to designers or not. Second question is about the current condition of data utilization. In other words, apart from conventional algorithmic data process approach, how do behavioural data is utilized in service design process. Understanding such facts and practice around behavioural data is important for the service design community and design practice in our era of big data and will contribute to discover future opportunities for DDD research.

This paper presents a systematic literature review of the design research, which utilise quantitative behavioural data in services design process. The research question addressed in the paper is: “How is behavioural data used in services design, and what is effective and valuable ways of using behaviour data for design? ” To answer this question, this literature study aims to provide an overall picture and its current tendency of the behavioural data used in design.

Method

The PRISMA statement was applied as our approach, the well-elaborated framework for systematic literature reviews (Moher et al., 2009). As the PRISMA statement targets medical research where terminology is static and rigorous, it might be difficult to completely follow the PRISMA framework in design research (Lame, 2019). Therefore, we modified the approach and conducted three phases: database searches, screening based on abstract, and qualitative synthesis. Literature was searched in August 2021 through a data repository, SCOPUS. Major design journals, international conferences, and the ACM library were chosen as target publishers. Table 1 shows the search terms used for the literature search. The terminology was carefully chosen based on the preliminary literature review so that the selected words could cover wider activities relevant to design activities on behavioural data beyond sensing and IoT data. This aimed at highlighting the characteristics of behaviour data around sensors and IoT. A total of 581 pieces of research were found during the first database search. The 536 articles remained after the eligibility check of the paper with the year of publications and publishers. Abstracts of the papers were collected and screened, and then full papers were analysed based on the five criteria (Table 2). The literature search and screening process identified 53 papers for the review, which was manually expanded to 57 in total with one paper regarding the use of data for user research and three articles of data-enabled design based on the existing knowledge of the authors.

Publisher	**Design Journals**	**Design conferences**	**ACM conferences**
Source title	Design Journals, Design Studies and International Journal of Design *1	International design conferences	ACM
Years	Not applied	2015 -	2015 -

Data related terms	“Behavioural data” OR "Data visualisation" OR "Personal Data visualisation" OR "IoT Data visualisation" OR "IoT" OR "data driven" OR "data driven design" OR "data enabled design"	
Design related terms	Not applied	Applied *2

Table 1. Words in systematic literature search

*1: “International Journal of Design” OR “design studies” OR “CoDesign” OR “Service Design” OR “Design Science” OR “Journal of Design Research” OR “Journal of Engineering Design” OR “Research in Engineering Design” OR “International Journal Of Design Creativity and Innovation” OR

*2: "co-design" OR "participatory design" OR "codesign" OR "empathy" OR "empathic design" OR “service design” OR "user research" OR "user understanding" OR "user centred design" OR "user centric" OR "service design" OR "human centred design" OR "reflection"

No.	**Criterion**
1	An article must be published in English
2	Full paper must be available
3	An article must NOT be a review research
4	An article must NOT address pure technology-related issues alone, such as IoT backend technology and detailed CAD design or be a simple report of developing IoT prototypes.
5	An article must use or discuss quantitative data for the early design phase, such as empathic understanding of users, understanding design contexts, and concept generation OR discussing the use of quantitative data or data visualisation for design research and practice.

Table 2. Selection Criteria

The selected articles were analysed in the following procedure. First, each article was summarised into two or three sentences, including key claims of the study. Then, each article was categorised with four coding schemes, which categories (1) data users (who viewed/used data), (2) data representation (what kind of data was used), (3) data visualization (how the data was visualised), and (4) time scope (whether the data visualisation real-time or static). Finally, the five authors cross-reviewed the notes, then mapped the articles into, using the KJ method (Scupin, 1997)

Results from the review

This section provides an overview of the 57 publications obtained from the systematic review process. The analysis focuses on the current practice of data utilisation in service design and the following subsections narrow the analysis considering the distinct aspects of behavioural data use in design.

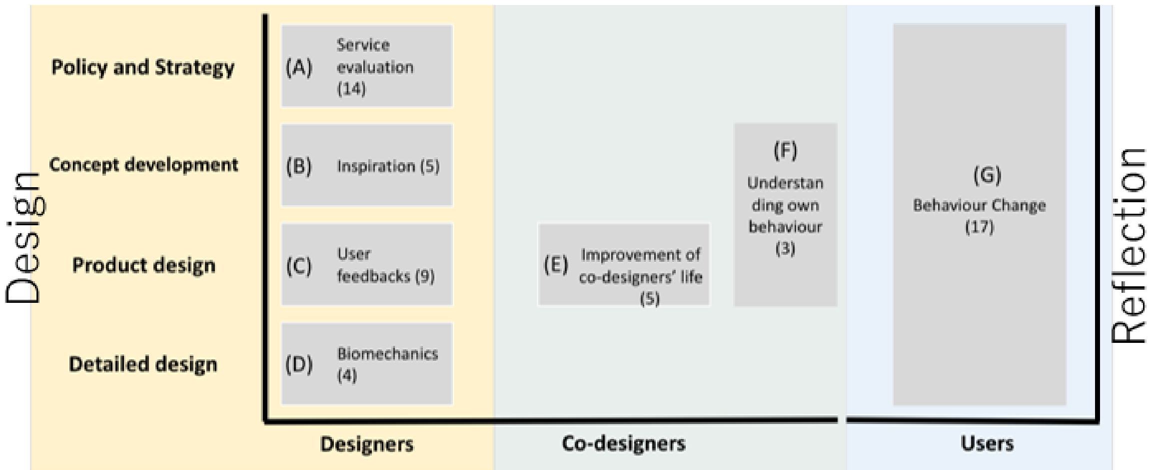

Figure 1. Spatial mapping of articles, using two axes of users and purposes

From an analytical perspective, this review paper focuses on two axes of *users* and *purposes*; (1) users indicate who is using behavioural data and for what purpose, and (2) purposes clarify what kind of data is collected, processed, visualised, and used for design. The two axes were set as two dimensions in the analysis, and the selected papers were spatially allocated (Figure 1). The horizontal axis represents three types of data users, and the vertical axis represents the purpose of behavioural data usage. The number shown in parentheses for each category is the number of defined papers.

Data users and their purpose

We identified three types of users: Users, Designers, and Co-Designers. Designers used behavioural data the most, featuring 32 papers, while Users used behavioural data with 17 pieces. In the five papers, data were used by Co-Designers, and three articles could not be clearly categorised between Users or Co-Designers.

The purpose is divided into two; one for design and the other for reflection. There are 37 papers (A-E in Fig. 1) that used behavioural data for design, and 20 papers (F and G in Fig. 1) for reflection. Eight papers (E and F in Fig.1) are categorised into overlapping areas, that is, areas used both for design and reflection. Among them, three papers (F in Fig.1) are used for reflection, but reflective thinking is explicitly used for design by designers. Looking at the papers on the area *for design*, in more detail, they can be classified into four detailed design areas. 14, five, nine and four papers dealt with strategy, concept development, product design, and detailed design, respectively.

Users utilized behavioural data for reflection

The analysis identified 17 papers that utilised behavioural data by Users, and they used behavioural data for reflection by accessing visualised data. The use of personal tracking devices such as Fitbit fell into this category. The reflection often aimed at changing the viewers' behaviours, which could be further divided into two categories: recalling and making sense of episodes. In our review, healthcare data visualisation was the most popular topic in this field, which is equivalent to 11 literatures such as Aseniero et al., 2020; Elsborg et al., 2020; Meyer et al., 2016; Tuna and Şener, 2015; Joung and Kim, 2021; Suryadi and Kim, 2019a. For example, data from Electrodermal Activity (EDA) sensors successfully provided a clue for anxiety patients to recall their daily life (Elsborg et al., 2020).

Apart from healthcare contexts, reflection based on behavioural data visualisation was used for understanding consumer behaviour in everyday life. Bergamaschi S. (2015) proposed a concept of dynamic product, which visualised energy resources' consumptions to make sense of their own consumption habits (Bergamaschi, 2015). Similarly, Ahn K., Kim K. O., Sung H. studied consumer behaviour and needs by understanding domestic consumption patterns (Ahn, 2015). These articles indicate user reflection's values through visualising behavioural data for their own sake. However, it is important to note that behavioural data were not utilised as primary data in the design process but for reflection.

Designers utilize behavioural data for design

The analysis identified 32 papers that utilised behavioural data by Designers in the service design process (DDD). The identified purpose could be narrowed down to four sub-categories; service evaluation (A in Fig.1), inspiration (B in Fig.1), user feedback (C in Fig.1), biomechanics (users' vital data) (D in Fig.1).

The articles which used behavioural data to support discussion and decision-making at service evaluation are the focus of 14 papers, allocated in policy and strategy (A in Fig.1). Text mining is used to elicit users' needs from online reviews for making strategy-level decisions (Han and Moghaddam, 2021; Shi et al., 2017; Suryadi and Kim, 2019b).

The articles on concept development (B in Fig1) included research developing data-based stimuli for concept development, such as providing analogical inspiration based on patent databases (Jiang et al., 2022; Sarica et al., 2021; Song et al., 2020). Yi Min Lim et al. (2021) developed an idea generation game, a Datastorming kit, consisting of open data cards, personal data cards, persona, and theme. The concept was qualitatively evaluated with students by generating service design concepts. (Yi Min Lim et al., 2021). Pothong et al., (2021) developed a game that elicited users' creativity and ideas regarding how data should be treated. Participants of the game were divided into two teams and negotiated to trade virtual objects representing data. One tool supported automated collection and optimisation of real-time data, while the other supported conscious collection and sharing of individual emotional data. (Pothong et al., 2021). The articles which used user feedback for product design (C in Fig.1) are the focus of nine papers (for example, Chaklader and Parkinson, 2017; Hou et al., 2019; Joung and Kim, 2021; Suryadi and Kim, 2019a). The data sources were online user review comments, and the studies proposed new algorithms to analyse data sources and verified the algorithms with specific cases, such as tablets (Hou et al., 2019) and smartphones (Joung and Kim, 2021). The four papers focus on the articles that used biomechanical measurements of the human body for detailed design (D in Fig.1). In the studies, data were collected by designated sensors such as motion sensors. The cyber-empathic design used embedded sensors to visualise user-product interactions, which was demonstrated by a case study visualising the distribution of forces in the shoe sole (Ghosh et al., 2017). Biomechanical aspects of user-product interactions were measured by motion captures and visualised for the designers' inspiration (Camere et al., 2015; Miehling & Wartzack, 2015; Wolf et al., 2019).

CoDesigners utilize behavioural data for design and reflection

Users sometimes collect, visualise, and analyse behavioural data as designers and contribute to the service design. Our analysis identified five papers that utilised behavioural data by such CoDesigners in the service design process (DDD) (E-Fig. 1).

For example, Routinoscope (Woo & Lim, 2020) installed sensors and actuators to create a DIY Smart Home at six private homes, and by browsing the visualised data obtained from the sensors, CoDesigners improved the system over continuous reflections. Through the three weeks in "the wild study (living lab)," family members as CoDesigners reviewed their routines and actions, which led to improving their own daily routines, recognising family challenges, and decreasing family arguments. Sensorstation by Denefleh (2019) explored the effect of smart sensors and services and their sensing data utilisation in a shared apartment. Users could set up sensors at any location of their own choice. Based on the collected and visualised data, future services for their own problems were explored through co-design (Denefleh et al., 2019). This design process has strong characteristics of CoDesign that a person as designer and user conducted co-design through reflection in action (Ehn, 1989) rather than collaboration between designers and users. As CoDesigners, they utilised their behavioural data to conduct reflection and design. By looking back own actions, CoDesigners reminded the situation when the behavioural data was collected, and they carried out the act of design by revitalising more concrete sensible memories as a person concerned.

This category also includes data-enabled design, which uses fewer data for product development, first proposed by Bogers et al. (2016). In data-enabled design, collected data from a target device was reviewed by the participants, who are the data owners and domain professionals such as medical doctors and designers (Bogers et al., 2016; van den Heuvel et al., 2020; van Kollenburg et al., 2018). The collected data through sensors was primarily targeted to improve the prototypes by providing an in-depth contextual understanding of user behaviours.

Lastly, the analysis identified three papers in which behavioural data were used for reflection by the data owner for design by designers. The behavioural data were personal data taken during the user research, such as interviews and used for reflecting and recognising unaware behaviour for contributing to the design. For example, in the experiment by Arvola (Arvola *et al.*, 2017), where participants were equipped with a tiny camera for recording the first-person perspective and a wearable device for collecting heart rate, each participant could recall his or her behaviours vividly by reviewing own behaviour data.

Characteristics of Data

Next, we look at the data characteristics of data, focusing on what kind of data is collected, processed, visualized, and used.

The two categories

The behavioural data in the 57 articles have been categorised into two kinds of data, Open Data and Private Data. Open Data is publicly accessible data, including online data such as posts, comments, and conversations on social media and comments on online review sites. In addition, open data also include public data such as surveys, traffic, and national census data. At the same time, Private Data is categorised as data taken through wearable and IoT sensors and includes limited accessed data such as individual activity data or classified public data, which is not available by the general third parties. As shown in Fig.2, in our review, 33 papers dealt with open data and ten papers dealt with sensor data.

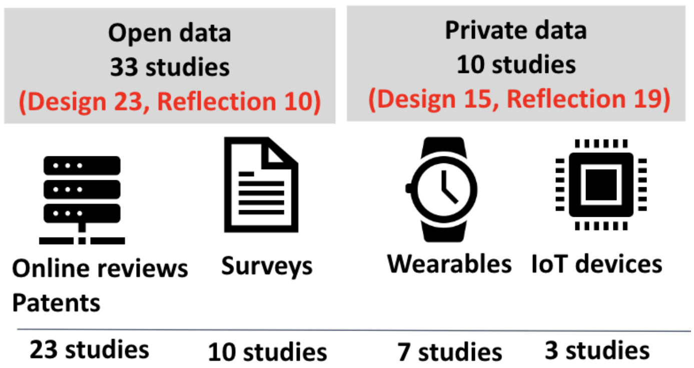

Figure 2. Types of data. *The total number of the studies in the figure does not match the number of reviewed papers due to overlaps or inability to classify.

Examples of Open Data were online reviews and government statistics such as populations (Burnap et al., 2016; Claes et al., 2017a). User review data on online review sites, such as Amazon, were often analysed to elicit user preferences (Joung and Kim, 2021) and user needs (Han and Moghaddam, 2021; Shi et al., 2017). Data on patent databases were also used to create creative stimuli through analogical inspiration (Jiang et al., 2022; Song et al., 2020) and product function recommendations (Deng et al., 2017).

Private data are taken by sensors such as wearable and IoT, which consisted of seven and three papers, respectively. The papers using personal data by sensors are overlapped with papers allocated in E and F in Fig1 and are often used for reflection. Behavioural data taken through sensors could also be used to propose a design solution for public space, where community data were anonymised, visualised, and utilised for community commons. Claes (Claes et al., 2017b) designed a system that encourages citizen participation in politics. The system visualises and displays citizens' behavioural data accumulated by communicative activities in a display set in a public space. Similarly, Puussaar (2018) proposed visualisation of the city data on a digital map by plotting public data of the municipality.

These community-related behaviour data are to be indirectly used for design and reflection, in which citizens and experts potentially become data users. However, in the current cases, it is not Users but Designers who conducted visualisation and utilised the behavioural data of the users.

Data Representation and Real-time-ness

Behavioural data has usually been visualised in various modalities such as texts, ordinal graphs, interactive dashboards, and three-dimensional tangible representations (Figure 3), such that the viewers can read data for their own purpose. Our analysis identified three, 13, 10, and two studies externalised its behavioural data within these data representations.

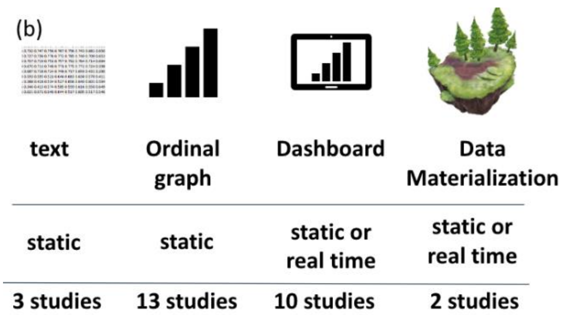

Figure 3. Data set representation. *The total number of the studies in the figure does not match the number of reviewed papers due to overlaps or unable to classify.

Among all, the ordinal graph representations and interactive dashboards were the most major visualisation representation of quantitative data (13 and 10 articles, respectively), and a few articles with text representations (three) and data materialisations (two). The texts and ordinal graphic representations visualise behavioural data in static ways, while dashboards and three-dimensional materialised representations sometimes offered real-time data visualisation.

Among all, a novel and unique approach to data representation, Data materialisation, has been suggested in two articles (Beghelli et al., 2019; Bergamaschi, 2015) in our studies. Aseniero et al. (2020) developed Activity River to visualise planned and recorded personal activities, and various visualisations of data methods as tangible forms, which Beghelli called Data Materialisation, have been explored (Beghelli et al., 2019). Giving a physical form to data provides the advantage of increasing engagement with data (Bergamaschi, 2015), as shown in an example of an artificial tree on a table, which swings influenced by the real-time wind speed taken from a meteorological agency.

Our analysis reveals that static data visualisation is still the most popular way to show time-consuming analysis results, such as text mining (Joung and Kim, 2021), despite the variety of available choices of data visualisations. At the same time, our analysis also indicates that choosing appropriate data representations is an emerging research interest. In other words, the right behavioural data visualisation choice can widen service design opportunities. For example, visualising community data in public spaces (Claes *et al.*, 2017a) and viewing personal data in a closed room (Denefleh *et al.*, 2019; Woo & Lim, 2020) have different constraints and purposes. An appropriate visualisation choice of community behavioural data might motivate citizens to commit to city planning (Claes et al, 2017b), while a key for personal data visualisation is the easiness of data understanding (Aseniero *et al.*, 2020). The modality of data visualisation and representations largely depends on the objectives of data visualisation and the type of data a study could capture. Moreover, static and real-time data visualisation is also a critical choice in visualising behavioural data. Real-time representation helps to comprehend behavioural data better, as shown in cases such as the materialisation of outside wind speed (Beghelli *et al.*, 2019) and everyday life routine patterns (Woo and Lim, 2020).

Data Analysis and Discussion

Due to the increased ease of access to IoT and wearable devices, there have been grand expectations for utilization of behavioural data (Bertoni, 2020; Kim et al. 2017). In our selection process, majority papers were excluded, among which only 57 papers met the evaluation criteria. We would argue one of the reasons is, as was discussed in Bertoni (2020), the direct users' behaviour data is scarce, and further scarce if we limited behavioural data from sensing devices.

The following two points were particularly characteristic in our analysis.

First, much of the research on behavioural data is related to the utilization of online data and it was used by designers. It is obvious that behavioural data including open data have not been utilized at most of its potentials. Despite the global interests towards behavioural data collected by IoT and wearable devices were hardly utilized in service design. Our analysis showed that the user-generated data used by Designers is often data from social networks and online reviews, and as also mentioned in Hou and Joung and Kim (Hou2019, Joung and Kim 2021), text mining is used dominantly as conventional analytic method. In other words, design research using behavioural data in response to the increase in IoT and wearable data has hardly been conducted, which is consistent with the findings of Bertoni (2020), Kim et al (2017) and others.

On the other hand, in our review, a few cases are found, in which behavioural data from IoT and wearables were used. In those cases, the behavioural data was viewed by Users, not only by Designers. We also found that when viewed by Users, the behavioural data was used for reflection rather than for design. This is because in most of the target studies, the purpose of using behavioural data is data visualization for behaviour change, and the original purpose of collecting data is not to utilize data for design. Among all selected paper, only eight papers are used for design by Users and CoDesigners. Among which, the core purpose of the three papers is reflection but also concerned for design as well, and the five papers concern design by CoDesigner. In the research by Arvola et al., personal reflection was partly used in product design. To iterate, in their research, personal data is used for users to recall their own experiences, and the result is passed to designers and the reflection based on behavioural data oriented toward product development. However, this case still did not achieve co-design, as Designers and Users took clearly separated task and Users cannot provide any opinions of influence on the design.

Secondly, our analysis showed that users' participation in design and users' participation in co-design with designers are untapped arena in DDD research of service design. Most of the existing design literature on behavioural data focuses on designers utilized the third persons' behavioural data or users reflected on their behaviour with their data.

Our analysis indicates an untapped opportunity of co-design research, using behavioural data in service design. In below, five advantages are discussed.

First, as Bertoni (2020) also shows, utilizing behavioural data of a service instead of the users' subjective opinions, could grant discovery of unexpected behaviours, which would allow an identification of untapped needs. Second, collecting valuable behavioural data is necessary to proactively plan and design. The regular collection of behavioural data from a service, especially in real-time, requires a proactive initiative from the users, facing setup costs, and maintenance costs. Thirdly, GDPR and other regulatory and common sense in society have increased the cost for dealing with service users' privacy if the third party use behavioural data. From privacy and personal information protection point of view, it is difficult to use personal data for design. Therefore, in this review, when personal information such as personal behavioural data is used, it was only when CoDesigners used their own behavioural data. CoDesigners can be a designer in unique position as they can utilize freely both publicly available data and their own data as input for design. Fourthly, it is beneficial for everyone to involve in design. We can see ourselves objectively by looking at our own behavioural data and can contribute more to the service design that we want. And finally utilizing with behavioural data means to promote DDD instead of Feeling Driven Design. This promotes mutual understanding through comparison with others, position, and recognition of differences.

Conclusion

This study has presented the result of a systematic literature review of the utilisation of quantitative behavioural data for design taken from IoT and wearable devices. The review identified 57 pieces of scientific literature in which data was used to identify behaviour in service. The behavioural data were used to reflect user behaviour and design service. The result clarified that using behavioural data by professional designers for design was predominant. At the same time, the result suggested limited behavioural data usage for co-design. Considering technological advancement in society and the increased extensive generation and use of behavioural data along with the increase of IoT and wearable devices in society, the utilisation of behavioural data more beneficially and ethically should attract more attention. Thus the potential of co-design should be addressed. Our literature review indicates that using behavioural data in the co-design process has a high potential of contributing to developing our service design community and thus should be promoted strategically and diligently.

Acknowledgments

References

Arvola, M., Blomkvist, J. and Wahlman, F. (2017), “Lifelogging in User Experience Research: Supporting Recall and Improving Data Richness”, The Design Journal, Routledge, Vol. 20 No. sup1, pp. S3954–S3965.

Aseniero, B.A., Perin, C., Willett, W., Tang, A. and Carpendale, S. (2020), "Activity River: Visualizing Planned and Logged Personal Activities for Reflection", Proc. Int. Conf. on Advanced Visual Interfaces, ACM, pp. 1–9.

Ahn K., Kim K.O., Sung H. (2015), A study on consumer trend and service innovation in Korean market, Proc. of ICED, pp. 097-108.

Beghelli, A., Huerta-Cánepa, G. and Segal, R. (2019), "Data Materialisation: A New Undergraduate Course for a Data Driven Society", Proc. of the Design Society: International Conference on Engineering Design, Cambridge University Press, Vol. 1 No. 1, pp. 2061–2070.

Bergamaschi, S. (2015), "Dynamic products: An instrument for Saving Resources. Improve User's Awareness Through Designing Product Experiences", Proc. of ICED. Vol 9. pp. 087–096.

Bertoni, A. (2020), "Data-driven Design in Concept Development: Systematic. Review and Missed Opportunities", Proc. of the Design Society: DESIGN Conference, Cambridge University Press, Vol. 1, pp. 101–110.

Bogers, S., Frens, J., van Kollenburg, J., Deckers, E. and Hummels, C. (2016), "Connected Baby Bottle: A Design Case Study Towards a Framework for Data-Enabled Design", presented at the Proc. of Designing Interactive Systems, ACM, pp. 301–311.

Bogers, S., van Kollenburg, J., Frens, J. and Djajadiningrat, T. (2016), "Data-Enabled-Design: A Situated Exploration of Rich Interactions", Proc. of Companion Publication on Designing Interactive Systems, ACM, pp. 45–48.

Burnap, A., Pan, Y., Liu, Y., Ren, Y., Lee, H., Gonzalez, R. and Papalambros, P.Y. (2016), "Improving Design Preference Prediction Accuracy Using Feature Learning", J. of Mechanical Design. DOI: https://doi.org/10.1115/1.4033427.

Camere, S., Schifferstein, H. and Bordegoni, M. (2015), "The experience map. A tool to support experience-driven multisensory design", Proc. of the 9th International Conference on Design and Semantics of Form and Movement.

Cantamessa, M., Montagna, F., Altavilla, S. and Casagrande-Seretti, A. (2020), "Data-driven design: the new challenges of digitalization on product design and development", Design Science, Cambridge University Press, Vol. 6. DOI:https://doi.org/10.1017/dsj.2020.25.

Chaklader, R. and Parkinson, M.B. (2017), "Data-Driven Sizing Specification Utilizing Consumer Text Reviews", J. of Mechanical Design, American Society of Mechanical Engineers Digital Collection, Vol. 139 No. 11. DOI:https://doi.org/10.1115/1.4037476.

Claes, S., Coenen, J. and Vande Moere, A. (2017a), "Empowering Citizens with Spatially Distributed Public Visualization Displays", Proc. of Companion Publication on Designing Interactive Systems, ACM, pp. 213–217.

Claes, S. and Vande Moere, A. (2017b), "The Impact of a Narrative Design Strategy for Information Visualization on a Public Display", Proc. of Designing Interactive Systems, ACM, pp. 833–838.

Denefleh, T., Berger, A., Kurze, A., Bischof, A. and Frauenberger, C. (2019), "Sensorstation: Exploring Simple Sensor Data in the Context of a Shared Apartment", Proc. of Designing Interactive Systems Conference, ACM, pp. 683–695.

Deng, Q., Franke, M., Hribernik, K., Thoben, K.-D. and et. al. (2017), "Exploring the integration of social media feedback for user-oriented product development", Proc. of ICED. pp. 453–462.

van Dijck, J. (2014), "Datafication, dataism and dataveillance: Big Data between scientific paradigm and ideology", Surveillance & Society, Vol. 12 No. 2, pp. 197–208.

Ehn, P. (1989) "The Art and Science of Designing Computer Artifacts, Scandinavian J. of Information Systems: Vol. 1: 1, 3.

Elsborg, M., Bruun, A. and Jensen, R.H. (2020), "Supporting Anxiety Patients' Self-Reflection through Visualization of Physiological Data", 32nd Australian Conference on Human-Computer Interaction, ACM, pp. 742–747.

Ghosh, D., Olewnik, A., Lewis, K., Kim, J. and Lakshmanan, A. (2017), "Cyber-Empathic Design: A Data-Driven Framework for Product Design", Journal of Mechanical Design, American Society of Mechanical Engineers Digital Collection, Vol. 139 No. 9. DOI:https://doi.org/10.1115/1.4036780.

Han, Y. and Moghaddam, M. (2021), "Eliciting Attribute-Level User Needs From Online Reviews With Deep Language Models and Information Extraction", J. of Mechanical Design, American Society of Mechanical Engineers Digital Collection, Vol. 143 No. 6, DOI:https://doi.org/10.1115/1.4048819.

van den Heuvel, R., Driesse, E., Dekker, M. and Calota, M. (2020), “Understanding routines around medicine intake through a data-enabled design approach”, Proc. of the Int. Symposium on Wearable Computers, ACM, pp. 139–142.

Hou, T., Yannou, B., Leroy, Y. and Poirson, E. (2019), “An Affordance-Based Online Review Analysis Framework”, Proc. of the Design Society: Int. Conf. on Engineering Design, Cambridge University Press, Vol. 1 No. 1, pp. 2457–2466.

Jiang, S., Hu, J., Wood, K.L. and Luo, J. (2022), “Data-Driven Design-By-Analogy: State-of-the-Art and Future Directions”, J. of Mechanical Design. DOI:https://doi.org/10.1115/1.4051681.

Joung, J. and Kim, H.M. (2021), “Approach for Importance–Performance Analysis of Product Attributes from Online Reviews”, J. of Mechanical Design, American Society of Mechanical Engineers Digital Collection, Vol. 143 No. 8. DOI:https://doi.org/10.1115/1.4049865.

Kim, H.H.M., Liu, Y., Wang, C.C.L. and Wang, Y. (2017), “Special Issue: Data-Driven Design (D3)”, J. of Mechanical Design, American Society of Mechanical Engineers Digital Collection, Vol.139. No.11. DOI:https://doi.org/10.1115/1.4037943.

King, R., Churchill, E.F. and Tan, C. (2017), Designing with Data: Improving the User Experience with A/B Testing, O’Reilly Media, Inc.

Kirk, A. (2016), Data Visualisation: A Handbook for Data Driven Design, SAGE.

van Kollenburg, J., Bogers, S., Rutjes, H., Deckers, E., Frens, J. and Hummels, C. (2018), “Exploring the Value of Parent Tracked Baby Data in Interactions with Healthcare Professionals: A Data-Enabled Design Exploration”, Proc. of the CHI Conf. on Human Factors in Computing Systems, ACM, pp. 297.

Lame, G. (2019), “Systematic Literature Reviews: An Introduction”, Proc. of the Design Society: Int. Conf. on Engineering Design, Vol. 1 No. 1, pp. 1633–1642.

Meyer, J., Kazakova, A., Büsing, M. and Boll, S. (2016), “Visualization of Complex Health Data on Mobile Devices”, Proc. of Workshop on Multimedia for Personal Health and Health Care, ACM, pp. 31–34.

Miehling, J. and Wartzack, S. (2015), “Strength mapping algorithm (SMA) for biomechanical human modelling using empirical Population data”, Proc. of ICED, Vol. 10, pp. 115–124.

Moher, D., Liberati, A., Tetzlaff, J., Altman, D.G. and Prisma Group. (2009), “Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement”, PLoS Medicine, Vol. 6 No. 7, p. e1000097.

Montecchi, T. and Becattini, N. (2020), “Design For Sustainable Behavior: Opportunities and Challenges of A Data-Driven Approach”, Proc. of the Design Society: DESIGN Conference, Cambridge University Press, Vol. 1, pp. 2089–2098.

Ortega, A.G., van Kollenburg, J., Shen, Y. Murray-Rust, D., Nedić, D., Jimenez, J. C., Meijer, W., Chaudhary, P.K.K. and Bourgeois, J. (2022). SIG on Data as Human-Centered Design Material. In Extended Abstracts of CHI Conf. on Human Factors in Computing Systems (CHI EA '22). ACM, Article 160, pp.1–4. DOI:https://doi.org/10.1145/3491101.3516403

Pothong, K., Speed, C., Catlow, R., Dixon, B., Morgan, E., Knowles, B., Newmarch, G., et al. (2021), “Deliberating Data-Driven Societies Through Live Action Role Play”, Proc. Of Designing Interactive Systems Conference, ACM, pp. 1726–1738.

Puussaar, A., Johnson, I.G., Montague, K., James, P. and Wright, P. (2018), “Making Open Data Work for Civic Advocacy”, Proc. ACM Hum.-Comput. Interact., ACM, Vol. 2 CSCW, pp. 1–20.

Sarica, S., Song, B., Luo, J., and Wood, K.L. (2021), “Idea generation with Technology Semantic Network”, Artificial Intelligence for Engineering Design, Analysis and Manufacturing: AI EDAM, Cambridge University Press, pp. 1–19.

Shi, F., Chen, L., Han, J. and Childs, P. (2017), “A Data-Driven Text Mining and Semantic Network Analysis for Design Information Retrieval”, J. of Mechanical Design, American Society of Mechanical Engineers, Vol. 139 No. 11. DOI:https://doi.org/10.1115/1.4037649.

Song, H., Evans, J. and Fu, K. (2020), “An exploration-based approach to computationally supported design-by-analogy using D3”, Artificial Intelligence for Engineering Design, Analysis and Manufacturing: AI EDAM, Cambridge University Press, Vol. 34 No. 4, pp. 444–457.

Suryadi, D. and Kim, H.M. (2019a), “A Data-Driven Methodology to Construct Customer Choice Sets Using Online Data and Customer Reviews”, J. of Mechanical Design, American Society of Mechanical Engineers Digital Collection, Vol. 141 No. 11. DOI:https://doi.org/10.1115/1.4044198.

Suryadi, D. and Kim, H.M. (2019b), “A Data-Driven Approach to Product Usage Context Identification From Online Customer Reviews”, J. of Mechanical Design, American Society of Mechanical Engineers Digital Collection, Vol. 141 No. 12. DOI:https://doi.org/10.1115/1.4044523.

Trauer, J., Schweigert-Recksiek, S., Onuma Okamoto, L., Spreitzer, K., Mörtl, M. and Zimmermann, M. (2020), “Data-driven engineering – definitions and insights from an industrial case study for a new approach in technical product development”, Balancing Innovation and Operation, Proc. of NordDesign 2020, The Design Society. DOI:https://doi.org/10.35199/norddesign2020.46.

Tuna, N.N. and Şener, B. (2015), “An Investigation of Diet Apps for Enhancing People’s Health and Wellbeing”, Proc. of ICED, pp. 209–218.

Wolf, A., Binder, N., Miehling, J. and Wartzack, S. (2019), Towards Virtual Assessment of Human Factors: A Concept for Data Driven Prediction and Analysis of Physical User-Product Interactions, Vol. 2019-August, Proc. of the Int. Conf. on Engineering Design. DOI:https://doi.org/10.1017/dsi.2019.410.

Woo, J. and Lim, Y. (2020), “Routinoscope: Collaborative routine reflection for routine-driven do-it-yourself smart homes”, Int. Journal of Design. http://ijdesign.org/index.php/IJDesign/article/view/3974.

Yi Min Lim, D., Yap, C.E.L. and Lee, J.-J. (2021), “Datastorming: Crafting data into design materials for design students’ creative data literacy”, Creativity and Cognition, ACM. DOI:https://doi.org/10.1145/3450741.3465246.