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SENSING BEHAVIOUR IN HEALTHCARE DESIGN

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Abstract

We are entering an era of distributed healthcare that should fit and respond to individual needs, behaviour and lifestyles. Designing such systems is a challenging task that requires continuous information about human behaviour on a large scale, for which pervasive sensing (e.g. using smartphones and wearables) presents exciting opportunities. While mobile sensing approaches are fuelling research in many areas, their use in engineering design remains limited. In this work, we present a collection of common behavioural measures from literature that can be used for a broad range of applications. We focus specifically on activity and location data that can easily be obtained from smartphones or wearables. We further demonstrate how these are applied in healthcare design using an example from dementia care. Comparing a current and proposed scenario exemplifies how integrating sensor-derived information about user behaviour can support the healthcare design goals of personalisation, adaptability and scalability, while emphasising patient quality of life.

Keywords: Human behaviour in design, Technology, Multi- / Cross- / Trans-disciplinary processes, Behavioural measurement, Pervasive healthcare

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1 INTRODUCTION

This work focuses on behavioural metrics within the topic of healthcare design, exploring opportunities presented by pervasive sensing. Designing healthcare systems of the future is a challenging task. These will need to serve the growing number of people in need of care, which together with technological advancement, is driving a shift towards a decentralised healthcare model that relies on home-based care and health management. At the same time, important healthcare goals should also be addressed, including:

- *personalised* care that takes into account patients' individual needs and desires
- *adaptive* care that aims to predict and prevent problems; and
- a focus on *quality of life* and wellbeing rather than a person's disease status alone.

This requires information about people's needs and quality of life to be gathered continuously and on a large scale, and shared throughout a diverse and dispersed stakeholder network. Methods commonly used in healthcare design to gather information about users' needs, such as interviews and observation, are too resource-heavy to be suitably scalable. These methods are typically used to inform a particular design iteration. For the future healthcare paradigm, however, such information should be gathered continuously and integrated into the system. That is, the information is required for operational action in an ongoing process as opposed to design action at a later point in time.

A promising avenue is the use of mobile sensors to gather data about human behaviour. Consumer products such as smartphones and wearables offer sensing capabilities that are increasingly being used for pervasive (or ubiquitous) computing in which data is collected continuously and unobtrusively from users. This data could provide valuable insights into people's behaviour and consequently their lifestyles and general wellbeing. Our aim is therefore to investigate these opportunities and how they might be applied in the design of future healthcare systems. The objectives addressed in this work are to:

- Review literature to find and summarise behavioural measurement approaches using activity and location data
- Demonstrate through an example scenario from dementia care how these might be applied in healthcare design to achieve important goals

Through these objectives, we contribute to the engineering design research community by providing a generic set of behavioural metrics measured with commonly available pervasive technology (e.g. smartphones or wearables) that serves a broad range of applications. These could provide a scalable, data-driven approach to understanding human behaviour in engineering systems.

The following section discusses the use of sensors to study human behaviour in engineering design research and provides a brief background to mobile sensing generally. This is followed by a review of literature to summarise common behavioural metrics obtained using activity and location data from smartphones and wearables. In section 3, current and proposed scenarios for dementia care are used to demonstrate how behavioural measurement approaches (such as those reviewed) could be applied in healthcare design to achieve the aforementioned healthcare goals. A discussion on this work's implications for engineering design, pinpointed limitations and future work is presented in section 4, followed by a conclusion in section 5.

2 SENSING BEHAVIOUR WITH PERVASIVE TECHNOLOGY

Engineering design research has long since examined human behaviour and its role in design. A distinction can be made between the behaviour of designers and that of users, customers or other stakeholders. Studying the behaviour of designers helps us to understand and improve the design activities or processes that they engage in (Lindemann, 2003). Studying the behaviour of users, customers or other stakeholders is an established approach towards gathering information about unmet needs or how people interact with designed artefacts. Understanding the behaviour of customers/users also plays a pivotal role in behavioural design, which describes the design of products or interventions that incorporate behaviour change strategies (Cash et al., 2016).

So far, sensor-based behavioural measurement has barely penetrated engineering design literature, with only a handful of examples. Sensor data on designer behaviour has been used for automatic detection of designers' emotional states to better understand design team interactions (Behoora and Tucker, 2015), and to relate design activities to physiological responses (Steinert and Jablokow, 2013). While both studies use sensors to measure behaviour, neither quite falls into the category of pervasive technology, which takes advantage of the portable, unobtrusive nature of the latest wearable and mobile devices. In this regard, an interesting case from the hearing aid industry is presented in a study on *instrumenting the user* (Aldaz et al., 2013). Here, behavioural data collected from hearing aids and smartphones is used to discover unidentified user needs, complementing existing qualitative methods. The data collected and the measures derived are somewhat specific to each of the examples described and may be difficult to transfer and apply in other design challenges. A far broader range of sensing approaches and analysis methods is presented in a survey of new digital technologies that can support design research, particularly for understanding users' needs and behavioural patterns(Thoring et al., 2015). We build upon this work by demonstrating how such sensing approaches can be applied in healthcare design. In this section, we review literature to collect examples of behavioural measurement in terms of common sensors, data, metrics and analysis approaches. First, a brief background on mobile sensing in healthcare and beyond is provided below.

2.1 Wearable and mobile sensing

Wearable sensors offer vast advantages over their bulky, cable-heavy predecessors and have over the years already seen expansive use in healthcare in applications ranging from chronic disease management, neurological disorders, and rehabilitation, to stress monitoring and emotion detection (Chan et al., 2012). The portability and unobtrusiveness of mobile sensors has enabled measurement to extend beyond the clinic into people's normal daily lives, blurring the boundary between medical devices and consumer products. Our smart devices (smartphones, wearables, tablets etc.) are packed with sensors that are increasingly being applied in pervasive healthcare and related fields (mHealth, ubiquitous computing) (Bardram, 2008; Fiordelli et al., 2013).

Sensor-derived behaviour measurement is also gaining momentum in other fields. The ability to gather rich behavioural data from smartphones allows insights into people's behaviour on a larger scale than ever before. The relevance of mobile crowd sensing for research in social sciences and other fields is recognised by Xiong et al. (2016), who present a general-purpose mobile sensing platform for such purposes. A decade earlier, wearable sensors from mobile phones were already being used to understand complex social systems using an approach termed *reality mining* (Eagle and Pentland, 2006). This work has been developed and built upon extensively over the years in research using mobile and wearable sensors to measure, understand and influence human behaviour and interactions – from mobility and daily cycles to friendship and social networks (Aledavood et al., 2015; Eagle et al., 2009; Stopczynski et al., 2014).

2.2 Behavioural measurement: sensors, data, features and analysis

When it comes to measuring and understanding human behaviour, information about *location* and *activity* is used extensively. This is not surprising, since our behaviour can largely be characterised by where we go and what we do. Location and activity information is also easily obtained using popular consumer products (including common smartphones) making it fit for generic use in a wide range of applications. Even where a particular case requires the use of other, more specialised sensors (e.g. microphones in hearing aids or blood glucose monitors for diabetes management), one can reasonably expect smartphones to be used either in conjunction with those sensors or independently by the user in everyday life. We will therefore narrow our focus to these two modalities.

Literature was reviewed to collect examples of behavioural monitoring using activity or location data from smartphones and wearables. These are used to describe common approaches in terms of the sensors used and data these yield, metrics calculated from this data, and how these have been analysed further. The results are summarised in Table 1.

2.2.1 Location

Location refers to the user's geospatial or position data, which can be collected from smartphones using GPS, possibly in combination with Wi-Fi, GSM, cell-tower or Bluetooth information. Location data typically comprises time-stamped positions (latitude, longitude) that are then used to extract a series of stops and moves termed *mobility traces*.

Various features can be calculated from a user's mobility traces. *Lifespace* refers to the size of the space in which a user carries out their daily life and includes metrics such as the total distance, area or perimeter covered (Tung et al., 2014). These have been applied together with measures of the maximum

or average distance from home (action-range), time spent outside of the home, and number of trips from home in studies involving the elderly (Giannouli et al., 2016) and people with dementia (Tung et al., 2014). A study on mental health using a similar set of mobility metrics further includes standard deviation of the displacements and analyses temporal patterns using a routine index that quantifies how different the places visited by a user are from one interval to another (Canzian and Musolesi, 2015).
Time spent at stops can be used to identify specific points of interest (POI's). In the SensibleDTU project, mobility traces from students are used to study human mobility by measuring geographical networks (POI's as nodes and paths between these as edges), time spent at POI's and the number of POI's visited over time (Cuttone et al., 2014). A study on social anxiety among college students specifically identifies work, home, social, religious and transportation places to calculate time spent at each type and the frequency of transitions between type pairs (Huang et al., 2016). Research involving reality mining groups places into work, home or other. Here, temporal patterns are analysed by examining how users move between these places over time to calculate entropy and derive *eigenbehaviours* that characterise their mobility behaviour or lifestyle (Eagle and Pentland, 2006, 2009). Measures based on location data (together with activity and other data) have also be analysed further for recognition of individual behavioural patterns to detect unusual events (Ahn and Han, 2013).

Table 1. Sensing user behaviour: common sensors, data, metrics and analysis from behavioural measurement studies using activity and location information.

	Sensors used	Data extracted	Metrics calculated	Further analysis
Location	*GPS Wi-Fi Bluetooth GSM	Positions (latitude, longitude) in a series of stops and moves	Total distance, area or perimeter Action-range Standard deviation of displacements Number of trips Time outside home Time at certain places (or types of place) Transitions between places	Routine index Geographical network analysis Entropy Eigenbehaviours Event detection
Activity	*Accelerometer *Gyroscope *Pedometer Magnetometer Barometer Microphone	Activity bouts for different activity states or types (at varying levels of detail) Steps Cadence Activity intensity Energy expenditure	Total steps Bout durations or ratios Number of bouts Transitions between activity states/types Variation in activity states/types	Relation to personal goals Event detection Change detection Temporal structure (trend gradient, probability density, similarity across time scales) Structural complexity

*Primary sensors used for the specified data collection purpose.

2.2.2 Activity

Smartphones contain several sensors that can be used to measure physical activity (or movement). Accelerometers are most common; however gyroscopes and pedometers are also used, as well as magnetometers, barometers and microphones (del Rosario et al., 2015). Numerous algorithms have been developed for these sensors to generate data such as steps, energy expenditure estimates, activity intensity, postures and gait characteristics. In turn, this data can be used to identify a wide range activity types or states at varying levels of detail (low- and high-level features): from active or sedentary states

to positions/movement (e.g. walking, sitting, standing and lying) or even types of daily activities, physical exercise or transport modes.
A common approach is to measure the duration and number of bouts for activity types. This is measured for walking bouts along with total steps and step time (cadence) to examine mobility among people with dementia (Tung et al., 2014). An example involving patients with chronic illness further relates the time spent in an activity to a personalised goal (van der Weegen et al., 2013). Duration ratios for walking, sitting and standing activities are analysed further to describe activity patterns in stroke rehabilitation by examining trend lines in these measures, specifically the gradient and offset (Derungs et al., 2015).
Monitoring changes in behaviour, e.g. based on lifestyle changes to meet a certain goal, is the focus of work describing a Physical Activity Change Detection (PACD) approach (Sprint et al., 2016). This uses activity type, intensity, duration and frequency to detect behaviour change and determine its significance. Patterns in activity are also analysed in a study that examines changes in activity behaviour in relation to health and ageing. This uses measures including activity type (sedentary, active, walking), intensity, steps and cadence. Variation within and transitions between these are also measured. Patterns are then analysed in various ways: univariate patterns are analysed using the probability distribution function (PDF), cumulative distribution function (CDF) and the detrended fluctuation analysis (DFA), which measures similarity of activity bouts across different time scales; multivariate patterns are analysed by modelling the activity pattern as a multi-state process and calculating structural complexity (Paraschiv-Ionescu et al., 2016).

The work described in this section comes mainly from technology sciences, which tend to focus on the path from sensing technologies to analysis methods, with less emphasis on integration into wider healthcare systems. Healthcare design could complement this by addressing the further steps and considerations necessary for implementation in practice. In the following section, we will shift to the role of healthcare design, demonstrating how these steps might unfold in the design of future dementia care.

3 DEMONSTRATIVE EXAMPLE FROM DEMENTIA CARE

As a demonstrative example of using sensor-based behaviour measurement in healthcare design, we will examine the design of a dementia care system. The rising prevalence of dementia due to an ageing population presents a considerable challenge in terms of both the burden this will place on healthcare systems and the quality of life for those affected. We will therefore investigate how pervasive sensing could be integrated into the design of a dementia care service to help sustain quality of life for a growing number of people with dementia, while meeting overall healthcare design goals of delivering personalised and preventative care.
Our focus is the process from the patient's first visit to the clinic onwards for those in the early stages of the disease. The target group includes people with a mild-to-moderate cognitive impairment who live at home in the community (as opposed to residents in a care facility). For this group, independence and social engagement are important aspects of quality of life, and home-based (distributed) care is particularly relevant.
Two scenarios are presented: current and proposed. The first is representative of current care practices and is based on our knowledge and experiences working closely with a dementia clinic in a Danish hospital for over 3 years in various research projects. The latter is an extension of the first, integrating behavioural measurement using pervasive technology.

3.1 Current scenario

Peter is a 71-year-old retired sales consultant who lives with his wife, Anne. Based on concerns both Peter and Anne have had about Peter's increasingly forgetfulness, their doctor refers them to a memory clinic. During their first visit to the clinic, Peter and Anne meet a nurse and a specialist doctor with whom they discuss at great length Peter's symptoms, general health and home life, especially regarding his functional capacity. Peter also undergoes several assessments and physiological tests. The test results and consultation notes are later discussed in a routine meeting among the clinic staff who together decide that Peter is in the early stages of Alzheimer's dementia.
Peter and Anne return to the clinic for an information meeting during which they are informed about Peter's diagnosis, a proposed course of medication to reduce his symptoms, and about support offered

by the clinic and municipality. After 3-4 weeks, the nurse calls to check up on Peter regarding the impact and any side effects of the medication. Peter and Anne visit the clinic again 3 and 9 months after Peter's treatment started according to a predefined schedule. Each time Peter's medication is again addressed and adjusted if necessary, his memory assessed, and his home life discussed. At the second control examination, it is clear that Peter's condition has declined significantly and the medication is no longer keeping his symptoms at bay. His memory impairment is considerably worse, and based on their interview, the specialist suspects that Peter has given up on many of his interests and become reclusive and depressed. Anne is noticeably worn out. She mentions that she called the dementia consultant in their municipality to ask for advice, but that by that time Peter was already spending most of his time alone at home and had no interest in meeting the dementia consultant or following her suggestions. The clinic staff talk to Peter and Anne about the future and suggest moving Peter to a care facility to relieve Anne and provide Peter with necessary support.

3.2 Proposed scenario

In this scenario, Peter owns a smartphone. He has used it for some time prior to the onset of his dementia for much the same purposes many of us do today: calendar, reminders and note-keeping; entertainment; social connection and communication.

At Peter's first consultation at the clinic, the nurse suggests an app for his phone to gather data about his behaviour, such as how much he goes out and how active or restful he is when home, explaining that this will aid their future discussions about his lifestyle and how this changes over time. She also recommends a smartwatch to wear instead of having to remember to carry his phone.

When Peter and Anne are informed about Peter's diagnosis, the specialist asks them about specific goals Peter has for his own independence and quality of life, for which Peter provides two:

1. Continuing to handle the grocery shopping, one of his main contributions to the household work
2. Maintaining an active social life, which he is concerned will decrease as his hobbies become more difficult for him to participate in.

They set up Peter's app to track measures related to his goals. For the first, they track how often he visits the local grocery store. For the second, they choose to track how much time he spends outside the home as an indicator of his social life. The specialist suggests a further measure: entropy in his daily pattern. The specialist has advised that Peter adhere to a routine already in the early stages of the disease, since maintaining this structure will help him to manage as his condition declines. Peter and Anne agree to share this information with the clinic as well as the dementia consultant from their municipality.

A phone check-up replaces a full assessment in the first control, since it is clear from the data being generated that Peter's condition is stable. Shortly afterwards, however, the app notifies the dementia consultant that Peter's trips to the grocery store have stopped and that he is spending more time at home. She arranges a visit to discuss any obstacles Peter is experiencing and how these might be overcome. She helps him set up a notification on his smartwatch to remind him of his grocery list as he arrives at the store, and suggests activities at the local care centre to replace hobbies he can no longer manage. Furthermore, she contacts the clinic and suggests bringing his next control forward. At the control, his assessment shows that his impairment has worsened, however he is performing satisfactorily in everyday life, particularly in relation to his own goals. They decide to continue as usual until his next control.

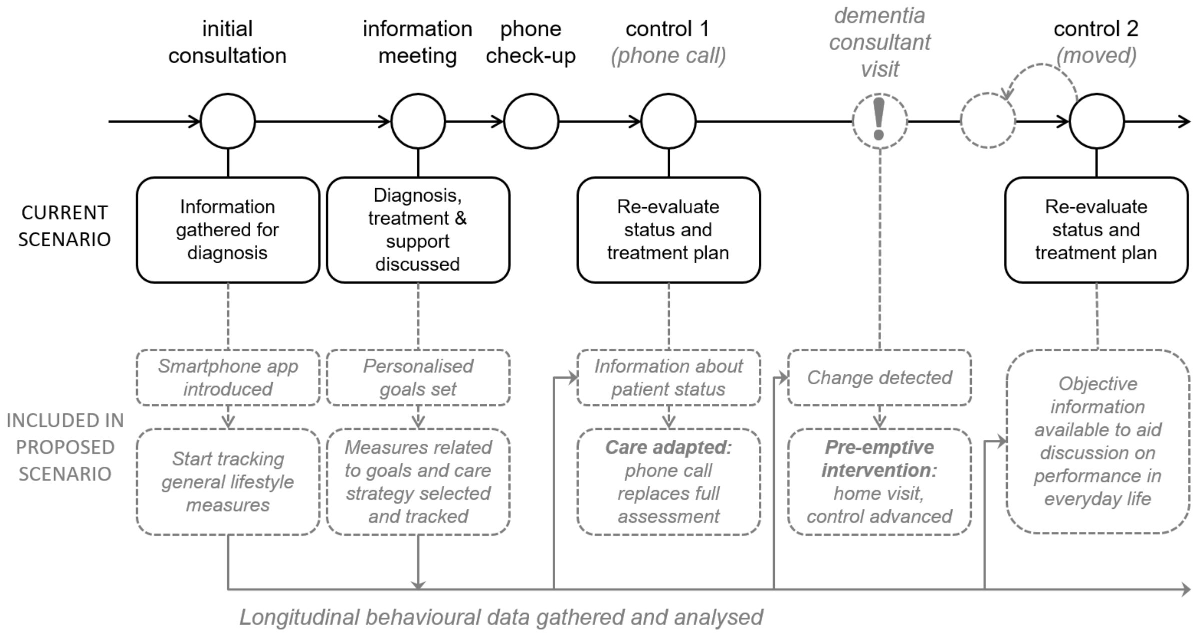

Figure 1. Process from first visit to the clinic until the second control showing the current scenario (black) and how this is extended or altered in the proposed scenario (grey).

An overview of how the current scenario is extended to include behavioural measurement in the proposed scenario is depicted in Figure 1. Core differences in the proposed scenario compared to the current scenario include:

- Continuous measurement
- Addition of objective information to assess lifestyle and behaviour
- Adaptation to the predefined care plan
- Specification of individual goals for quality of life in the care strategy

3.3 Comparing the two scenarios in relation to healthcare design goals

Comparing the proposed scenario to the current scenario demonstrates how behavioural sensing can be used to meet key healthcare design goals listed in the introduction.

Personalised, patient-centred care:
An example of personalised care demonstrated in the proposed scenario is the selection of features according to the patient's individual goals. Furthermore, information provided through behavioural measurements helps healthcare professionals to make suggestions based on patients' specific needs or lifestyle, for example the use of a smartwatch notification when Peter stops grocery shopping.

Adaptive and pre-emptive care
In the current scenario, information about the patient's condition is provided through assessments and patients' (or caregivers') perceptions, with long intervals between inputs. In contrast, the behavioural sensing provides continuous, objective information far better suited to early detection of an event or decline. This enables the preventative care model described in which Peter's decline in performance is detected early enough for an intervention (home visit from the dementia coordinator) and adaptation to his care strategy (control brought forward) help prevent his transfer to a care facility.

Scalability (and resource efficiency)
In the proposed scenario, pervasive technology generates vast information without relying on patients and their caregivers to actively report on events and behaviours nor on input from healthcare professionals. Furthermore, insights into Peter's lifestyle can aid discussions about his performance, allowing healthcare professionals to ask targeted questions that could reduce the time spent trying to understand how his behaviour is changing.

Emphasis on quality of life and wellbeing
In the proposed scenario, behavioural sensing is used to measure aspects of the patient's wellbeing to complement information about symptoms and medication response. This shifts the focus from functional capacity to performance in everyday life.

4 DISCUSSION

We have presented a generic selection of behavioural metrics and demonstrated their application in the example of designing pervasive dementia care. We will now discuss the importance of this work for healthcare design and beyond to engineering design research and practice generally, and pinpoint important limitations and areas for further study.

4.1 Bringing healthcare design into the conversation on pervasive sensing

The concepts presented in this work (sensing behaviour) have to date remained predominantly within the domain of technology sciences. The considerable progress made in these fields is of marked importance and is driving a revolution in healthcare. However, within the bounds of these fields, the focus remains mainly on the technology and information systems. Bringing this topic to the healthcare design agenda could accelerate progress and implementation in practice by including a holistic systems perspective and service design focus. This work contributes by bridging technology and design domains and promoting the adoption of behavioural sensing in design research, particularly for healthcare.

4.2 Implications for engineering design beyond healthcare

The generic, widely applicable behavioural measures presented in this work provide a starting point for engineering design researchers and practitioners to adopt data-driven approaches to understanding human behaviour. There are countless opportunities for monitoring behaviour to support engineering design research. The behavioural design process presented by Cash et al. (2016) includes several steps that require information about behaviour (e.g. defining a behavioural problem, field work and iterative testing of an intervention). Design of transport systems, smart cities and other engineering systems can be supported by information on population behaviour using mobile crowd sensing approaches. These combine sensor data with data from social networks to gather and share various types of information such as location, context, feelings and opinions, traffic conditions or pollution levels (Guo et al., 2015). Since studying complex sociotechnical systems is at the root of engineering design research, such tools for understanding human behaviour could greatly advance the field.

4.3 Limitations and future work

This work uses scenarios to present a concept and demonstrate its potential. Although this method was informed by close collaboration with experienced healthcare professionals, the proposed scenario should be tested in practice before further conclusions can be drawn about its benefits for healthcare design. Real-life testing is recommended to overcome the following limitations:

- It is unknown whether the level of use of the technology among people with dementia would be sufficient to generate the required data.
- The behavioural metrics presented are often measured using data collected under controlled conditions that may not represent real life (even "real-world" data collection tends to occur under strict protocols, e.g. specific device placement or use instructions).
- Further evidence is required to determine the impact of using behavioural sensing in healthcare design for the goals described (personalisation, adaptability, scalability, focus on wellbeing). While potential advantages are put forward, a thorough evaluation is beyond the scope of this work.

While we have focused specifically on activity and location data from smartphones or wearables, this can be combined with numerous other data sources. Future work should consider the opportunities presenting by sources such as: user interactions with the device; features based on social activity (e.g. calls and texts); and experience sampling, which utilise the pervasiveness of smartphones to collect information from users about their experiences in-the-moment (Aldaz et al., 2013).

5 CONCLUSION

This work addresses the need for scalable, data-driven approaches to measuring and understanding human behaviour in the design of future healthcare systems. As our main contribution, we present a generic set of behavioural metrics and a simple, conceptual description of their application in healthcare design.

Literature is reviewed to identify behavioural measurement approaches based on activity and location data that can be gathered using smartphones and wearables. These are used to present a collection of behavioural metrics, along with common sensors and data used to calculate these and examples of further analyses.

One healthcare area that could benefit from behavioural monitoring is dementia, which is increasing in prevalence and placing a large burden on healthcare resources. We have demonstrated through two scenarios (current and proposed) how using behavioural measurement in the design of a pervasive care system for dementia could help to achieve important healthcare design goals including personalisation, adaptive/pre-emptive care, scalability and a focus on quality of life.

The behavioural sensing approaches described could support a wide range of healthcare design challenges beyond dementia in future as we make the transition towards connected, distributed healthcare systems. Insights into human behaviour provided by continuous, objective measurement could further support the design of many other engineering systems.

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