Developing In-Textile Health Monitoring Systems with Custom Chiplets
(Technical Topic)

Leveraging the Technology Acceptance Model to Promote the Long-Term Use of Smart Wearable Devices
(STS Topic)

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By
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On my honor as a University student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments.

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Introduction

According to The Centers for Disease Control and Prevention (CDC), heart disease has been the leading cause of death in the United States for over seven decades, while other chronic illnesses such as chronic lower respiratory disease, kidney disease, and diabetes are all among the top ten killers in America (Heron & Anderson, 2016; Xu et al., 2021). With the growth of the internet of things and recent breakthroughs in machine learning, researchers have turned towards wearable electronic devices as a way to better diagnose, monitor, and manage these lethal diseases. In particular, heart disease, COPD, kidney disease, and diabetes can all be monitored using sensors mounted on wearable smart devices (Huang et al., 2022; Rodriguez-León et al., 2021; Tiwari et al., 2021; Wieringa et al., 2017). Furthermore, when wearable sensor data is analyzed using machine learning techniques, it's possible to predict events such as rehospitalization with comparable accuracy to conventional clinic measurements due to the long-term nature of mobile monitoring (Dunn et al., 2018).

Despite the enormous potential of wearables for health monitoring applications, these technologies have yet to live up to their transformational promise due to inconsistent use and high abandonment. In fact, Lee & Lee (2017) found that as many as 50% of users stopped wearing their smart devices weeks after purchase, while Hermsen et al. (2017) observed that 84% of FitBit users stopped wearing their trackers after less than a year. Both studies cited inconvenience, mistrust in measurements, and technical issues (battery life) as primary causes for abandonment.

From the literature, it's evident that well-designed, wearables-based health monitoring systems could revolutionize healthcare by alerting patients and their medical teams of life-threatening diseases. For such systems to be effective, users must wear these devices consistently over the long term, and the perceived convenience, accuracy, and usefulness of these devices must be increased. To achieve these improvements over the state of the art, my team proposes designing microchip-based, in-textile health monitoring systems as our technical project. As our STS topic, we intend to evaluate the consumer adoption of smart clothes using the Technology Acceptance Model developed by Davis (1989) and leverage this understanding to develop a set of guidelines for designing textile-based wearable technologies with high retention rates.

Technical Topic: Developing In-Textile Health Monitoring Systems with Custom Chiplets

Throughout the late 2010s and early 2020s, there have been numerous attempts at creating smart garments with temperature, sweat, and neural sensing capabilities (Loke et al., 2021; Wu et al., 2018; Yin et al, 2021). While these works resulted in functioning technical systems, they suffer from the use of discrete, bulky components and rigid batteries, rendering them less effective for day-to-day use. Advances in ultra-low power microchips, fabric batteries, and conductive textile infrastructure have yielded smaller, flexible components. These new technologies are more conducive to comfortable and seamless textile integration, paving the way for minimally invasive and unobtrusive textile-based health monitoring systems (Wu et al., 2021; Liu et al., 2023). In this section, I will outline challenges regarding computation and communication within the context of smart garments and highlight how existing works provide a platform from which to build on.

Fundamentally, one principle underlies the main challenge with designing chips-based smart clothing: in order for smart clothes to feel natural and comfortable, there must be no large rigid components integrated into the fabric. Indeed, most functions that a smart garment would need to perform in terms of computation, communication, and data storage are quite easily achieved using conventional microchips; however, these circuits are too large (> 1 cm/side) and too power hungry (on the order of Watts) to be integrated onto a textile comfortably (Yin et al., 2021; Yoke et al., 2021). To accommodate this basic area constraint, my team's approach is to disaggregate the components typically found on a single larger chip and create a distributed system of smaller chiplets that function together as a single computer. While making a single small chip is relatively straightforward, designing a network of sub-millimeter-scale chips that function as one system is challenging.

To understand how the area constraint of in-textile chiplets imposes system-wide challenges, it is instructive to look at the floorplan of a chip designed for textile integration. Figure 1 shows a die photo of a chip designed by my group, which is a 600 micron square.

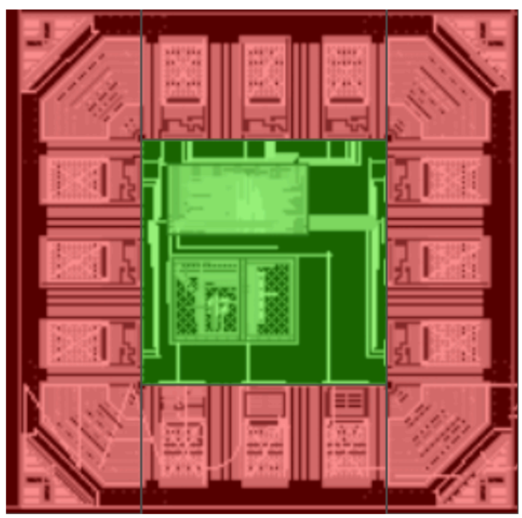

Figure 1. Floorplan of a Chip for Textile Integration (Created by Author). This image is a bird's-eye view of a chip designed by my technical group. Although the total chip area is 600 µm by 600 µm, only ¼ of this area can be used for any purpose (shown in green). The remaining area must be dedicated to special-purpose input/output circuitry (shown in red).

The section of the image highlighted in red represents the area used for input/output circuitry. This portion of the chip cannot be used to perform any computation or data storage. The remaining green area is the so-called “active area” and can be used for any purpose. Because the die is so small, the proportion of usable active area to total area is just one quarter, whereas this ratio is typically much greater than one half (Weste & Harris, 2010). This has severe implications for computation and communication.

In conventional computer architecture, one primary way to accelerate computation is to design hardware that can “multitask.” In reality, this means that certain parts of the chip are duplicated so that multiple copies of the same function can be used at the same time. While extremely effective at increasing the computational power of the computer, this technique is area-intensive: the total area (and energy) increases approximately linearly with the computation capability (Weste & Harris, 2010). In the context of textile systems, this traditional approach may not work due to the aforementioned area constraints. An alternative that my team is considering is to replace a single, larger chip with several copies of a smaller chip, duplicating the desired component on each smaller chip. Functionally this might work, but there are performance limitations that occur as a result of the small size required for textile-integrated chips.

On conventional computers, communication channels between different components typically use over eighty wires to link two functional units (Harris & Harris, 2015). For the chip shown in Figure 1, the maximum number of data signals entering or leaving the chip is nine. As part of our planned system, we intend to use a communication scheme called the Bypass Serial Peripheral Interface (SPI) to connect chips serially wire three wires, based on the work of Liu et al (2023). To hide the latency incurred by performing data transfers serially as opposed to in parallel, we propose a novel scheme of operating the peripheral interface at a much higher frequency than the core. Specifically, it must be fast enough such that in one clock cycle in the core’s clock domain, the peripheral interface can transmit or receive an entire 32-bit data packet.

Our deliverable for this project consists of two chips. The first, called the System-on-Chip will be responsible for computation and overall system management. The other chip will be a memory chip that is responsible for data storage and communication. Using the Bypass SPI scheme described above and other novel techniques, we plan to deliver chips that can be integrated into clothes to function as a single, cohesive system for health data sensing applications.

STS Topic: Leveraging the Technology Acceptance Model to Promote the Long-Term Use of Smart Wearable Devices

In spite of their health tracking capabilities, conventional wearable electronics have long faced issues of low adoption and abandonment. Researchers have found that intrinsic motivation loss, perceived measurement inaccuracy, tracker discomfort, charging discomfort, and lack of visual appeal are among the top ten reasons cited for abandonment (Attig & Franke, 2020). As technological advances begin to enable smart textile systems, consumers may find these devices more appealing and easier to adapt into their routine for health monitoring due to the unobtrusive and discreet nature of smart clothes. However, if system designers do not learn from the failures of conventional wearable devices, textile-based health monitoring systems still may not be widely accepted (Xu et al., 2022). In this section, we consider some of the reasons why users report abandoning wearables and introduce Davis's seminal Technology Acceptance Model (1989), a framework for understanding consumer acceptance of technological advancements. Ultimately, we hope to use this framework to develop a set of guidelines for designing smart clothes to promote long-term use.

Usability concerns are one of the primary reasons cited for abandoning wearable devices. Specifically, surveys of users who have abandoned fitness trackers have found that former users tend to agree with statements along the lines of "I don't find it useful" (Fadhil, 2019). Furthermore, about 60% of former users responding to another survey indicated that they believed that the long term monitoring features were not useful (Maher et al., 2017). Still others found that the web applications and smartphone applications associated with these devices had low usability or required too much mental effort to use consistently (Coorevits & Coenen, 2016; Epstein et al., 2016). Over a third of participants in one study identified tracking discomfort, charging discomfort, device or app inconvenience, or lack of visual appeal as among their reasons for abandoning a conventional wearable device (Attig & Franke, 2020). In summary, the existing literature suggests that a perceived lack of usability or usefulness is among the main motivations for users abandoning their wearable devices.

The empirical evidence that users abandon wearable health devices due to usability and usefulness concerns is highly consistent with the Technology Acceptance Model (TAM) (Davis, 1989). TAM is a well-regarded theory of consumer attitudes and behavior towards adopting new technologies. A visualization of this model is shown in Figure 2.

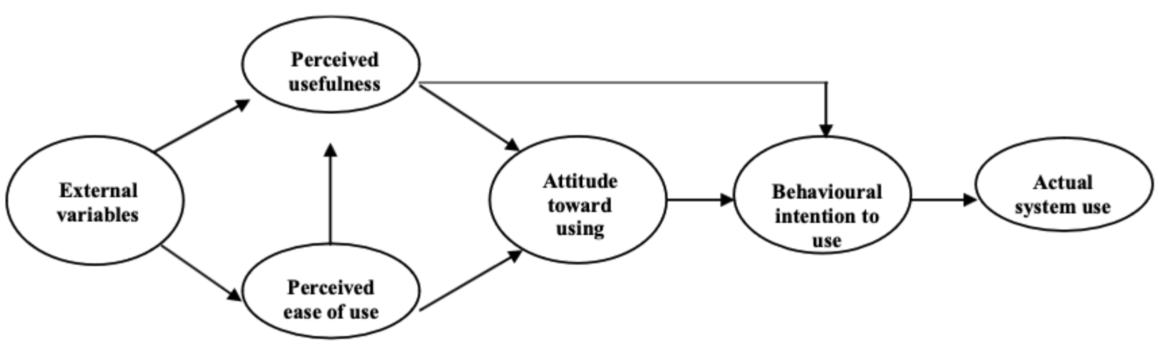

Figure 2. The Technology Acceptance Model. This visualization of TAM shows how perceived ease of use impacts perceived usefulness. Moreover, it illustrates how both factors ultimately determine actual system use (Kalantari, 2017).

TAM contends that two major factors are primarily responsible for determining the actual use of a system: perceived usefulness and perceived ease of use. In Davis's words, perceived usefulness is "the degree to which a person believes that using a particular system would enhance his or her job performance," whereas perceived ease of use "refers to the degree to which a person believes that using a particular system would be free of effort" (Davis, 1989, pp 320). Although Davis initially proposed his framework in the context of technologies in the workplace, it seems reasonable that the same framework could be applied to technologies used in a non-professional context such as wearable devices for health applications.

It's self-evident that in order for a textile-based wearable device to succeed at long term health monitoring, the device must be designed in such a way that avoids the weakness in perceived usefulness and ease of use of conventional wearables. For my STS research, I plan to study the adoption failures of past wearables using the TAM framework. From this analysis, I hope to conceive of a set of guidelines for designing wearable devices with the goal of improving user retention rates and decreasing abandonment.

Conclusion

My technical project should result in the creation of a chips-based, in-textile health monitoring system with applications to long-term diseases like cardiovascular disease, diabetes, COPD, and kidney disease. Because the success of such a system depends entirely on consistent, long-term monitoring, my STS research will analyze the failures of previous wearable systems using the TAM framework in order to determine guidelines for future wearables with improved retention rates. If successful, my technical project will enable patients to better manage their chronic illness without burdening them with cumbersome wearable devices and may lessen the frequency of doctor check-up appointments. A successful STS deliverable would entail a set of guidelines for designing wearables devices that results in lower abandonment rates through the mechanisms of improved perceived usefulness and perceived usability.

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