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Customer views on AI-assisted screening of cardiovascular disease in an optical retail setting

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Abstract

Retinal imaging combined with artificial intelligence (AI) has shown potential to detect biomarkers of systemic diseases such as cardiovascular disease (CVD) from routine eye images. While most oculomics research has focused on validating model performance in clinical settings, little is known about how such AI-based screening is perceived by customers, especially when delivered in a non-clinical, retail environment. This thesis investigates customer acceptance of an AI-assisted CVD risk screening service piloted at Silmäasema, a Finnish optical retail chain by addressing three research questions: how customers perceive the AI-based screening, what factors influence its acceptance, and what operational implications it holds for optical retail providers.

A quantitative, cross-sectional survey was administered to 184 participants. The questionnaire measured constructs including trust, explainability, perceived usefulness, understanding, appropriateness of the retail setting, and behavioural intention. Data were analysed using descriptive statistics, subgroup comparisons, correlations, and multiple linear regression.

Findings indicate broadly positive attitudes toward the service: respondents viewed the screening as useful, a natural extension of routine eye exams, and appropriate for the retail setting, while strongly expecting professional oversight of AI-generated results. Demographic characteristics (age, gender, education) shaped general technology and AI disposition but had little effect on evaluations of the service itself. Wearable-technology use was associated with more favourable evaluations of the service. Regression analyses showed that general trust in AI in healthcare and technology attitude were the strongest predictors of trust and intention to use the service. A gap emerged between customers' desire for explainability and their actual understanding of how AI was used.

The findings suggest that optical retail settings can serve as a viable, low-threshold channel for AI-based preventive screening, provided that clear communication, human oversight, and trust-building measures accompany the technology. The study contributes empirical evidence on customer-facing AI acceptance in a novel retail-health context and offers practical guidance for providers considering similar service innovations.

Keywords oculomics, artificial intelligence, technology acceptance, healthcare

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Tiivistelmä

Silmänpohjakuvauksen ja tekoälyn yhdistäminen on osoittanut mahdollisuuden systeemisten sairauksien, kuten sydän- ja verisuonitautien (CVD) riskien arviointiin silmänpohjakuvista. Aiempi tutkimus okulomiikan tutkimusalalla on keskittynyt pääosin mallien suorituskyvyn mittaamiseen, ja tieto ihmisten suhtautumisesta teknologiaan on jäänyt vähäiselle. Tämä diplomityö tutkii asiakkaiden suhtautumista tekoälyavusteiseen CVD-riskin arviointiin, jota pilotoitiin Silmäasemalla. Työssä tutkitaan, mitä asiakkaat ajattelevat tekoälypohjaisesta seulonnasta, mitkä tekijät vaikuttavat sen hyväksyntään, sekä millaisia operatiivisia vaikutuksia palvelulla on optisen alan palveluntarjoajille.

Diplomityön empiirinen osuus perustuu kvantitatiiviseen tutkimukseen. Kyselytutkimukseen osallistui 184 Silmäaseman asiakasta. Kysely mittasi muun muassa asiakkaiden luottamusta ja käyttöaikomusta sekä palvelun selitettävyyttä, koettua hyödyllisyyttä, ymmärrettävyyttä ja ympäristön soveltuvuutta. Aineistoa analysoitiin tunnusluvuin, ryhmävertailulla, korrelaatioanalyysillä ja lineaarisella regressiolla.

Tulokset osoittavat pääosin myönteistä suhtautumista palveluun: vastaajat pitivät seulontaa hyödyllisenä, luontevana osana silmätarkastusta ja optikkoliikeympäristöön sopivana, mutta toivoivat vahvasti ammattilaista tarkistamaan tulokset. Demografiset tekijät (ikä, sukupuoli, koulutus) selittivät eroja yleisissä teknologia- ja tekoälyasenteissa, mutta eivät itse palvelun arvioinnissa. Puettavan terveysteknologian (esim. älysormus ja -kello) käyttö oli yhteydessä myönteiseen suhtautumiseen palveluun. Regressioanalyysit osoittivat, että yleinen luottamus tekoälyyn terveydenhuollossa sekä teknologia-asenne ennustivat vahvimmin luottamusta ja käyttöaikomusta. Asiakkaiden toive selitettävyydestä ja heidän todellinen ymmärryksensä tekoälyn toiminnasta erosivat selvästi toisistaan.

Tulokset viittaavat siihen, että optikkoliikkeet voivat toimia matalan kynnyksen väylänä tekoälypohjaiselle ennaltaehkäisevälle seulonnalle, mikäli teknologiaan yhdistetään selkeä viestintä, ammattilaisten valvonta ja luottamusta rakentavat toimenpiteet. Tutkimus tuottaa empiiristä tietoa asiakaslähtöisen tekoälyn hyväksynnästä uudessa ympäristössä ja tarjoaa käytännön suuntaviivoja vastaavia palveluinnovaatioita harkitseville toimijoille.

Avainsanat okulomiikka, tekoäly, teknologian hyväksyntä, terveydenhuolto

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Abbreviations

CVD	Cardiovascular disease
AI	Artificial intelligence
IT	Information Technology
OCT	Optical coherence tomography
TAM	Technology Acceptance Model
UTAUT	Unified Theory of Acceptance and Use of Technology
SDL	Service dominant logic
VIF	Variance inflation factor

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1 Introduction

Sight is widely regarded as the most valued of the human senses, and the fear of losing it is a powerful motivator: people often attend eye examinations more frequently than other healthcare providers (Toikkanen, 2024). As a result, retinal imaging, which is used to diagnose conditions such as glaucoma and diabetic retinopathy, has become a routine part of preventive eye care, thus generating large volumes of retinal images. In recent years, artificial intelligence has advanced to the point where it can detect subtle patterns in medical images that may be hard to discern with the naked eye (Ghenciu et al., 2024). Together, these two developments point to an interesting possibility: the retinal images already captured during routine eye examinations may reveal more than the health of the eye itself. The term *oculomics*, introduced by Wagner and colleagues (2020), describes identifying biomarkers associated with systemic diseases such as cardiovascular disease, neurodegenerative disorders, and chronic kidney disease from retinal images. This matters at a population level: for example, cardiovascular disease is the leading cause of death in Europe, making accessible early detection a public health priority (European Commission. Directorate-General for Health and Food Safety, 2025).

The economic burden of cardiovascular diseases is considerable, with an estimated annual cost of €282 billion to the European economy (European Commission. Directorate-General for Health and Food Safety, 2025). Traditional cardiovascular screening is resource-intensive, and typically requires laboratory tests, specialist consultations, and multiple clinical visits. These processes can be costly, time-consuming, and out of reach for people who do not regularly engage with healthcare services. Oculomics offers a promising alternative, providing a non-invasive and potentially low-cost method for identifying risk markers via routine retinal imaging (Ghenciu et al., 2024). Combined with AI-driven analysis, it could enable large-scale screening and lower the threshold for preventive care, thus reaching more people and detecting disease early on.

Current research on AI-based oculomics has largely focused on validating the technology and algorithms and testing them in clinical settings (Ghenciu et al., 2024; Guo et al., 2025). Studies have investigated model performance, training data requirements, and the ability to predict specific risk factors or disease outcomes (Arnould et al., 2023; Hu et al., 2023). While these studies demonstrate technological feasibility, they predominantly examine controlled medical environments and clinical workflows. Beyond hospitals, optical retail environments may offer a significant opportunity for oculomics-based services. Optical retailers typically have extensive geographic coverage, existing imaging equipment, and a workforce trained in eye examinations.

This setting could therefore reach a broader population with screening services. Similar screening initiatives in non-traditional healthcare settings, such as pharmacies, have demonstrated positive user feedback (Fonseca et al., 2021; Rohla et al., 2016), suggesting that alternative service delivery models could increase access to preventive screening (Willis et al., 2014).

While the technological potential of AI-driven screening services has been recognized, its practical adoption depends on user acceptance. Public attitudes toward AI in healthcare vary, and concerns regarding trust, accuracy, and data use may influence uptake (Kauttonen et al., 2025; Richardson et al., 2022). Additionally, delivering healthcare services in non-traditional settings, such as optical retail stores, may raise further concerns or uncertainties among users. While research has examined the predictive performance of AI-based retinal biomarkers, there is limited evidence on real-world service implementation and user perceptions in retail healthcare contexts.

This thesis aims to investigate the potential of AI-driven oculomics-based cardiovascular disease screening in optical retail settings, with a particular focus on customer acceptance. The study is conducted as part of a pilot project by Silmäasema, a Finnish optical retail and eye care clinic chain. The research questions are as follows:

Research questions:

RQ1:	How do customers perceive the AI-based cardiovascular screening in optical retail settings?
RQ2:	What factors influence acceptance of such services?
RQ3:	What operational implications does the implementation of oculomics screening have for optical retail providers?

To address these questions, this thesis adopts a quantitative research approach and surveys customers. Additionally, an analysis of existing literature and industry practices is performed.

The remainder of this thesis is structured as follows. In Chapter 2, the relevant literature on AI in healthcare, oculomics, and technology acceptance is presented. The research methodology of this thesis is described in Chapter 3. Chapter 4 reports the results of the survey. Chapter 5 discusses the results in relation to existing research, practical implications, limitations, and directions for future research.

2 Literature review

This section reviews the literature relevant to AI-based CVD risk screening in an optical retail setting and customer acceptance of the service. It begins with an overview of artificial intelligence in healthcare, then covers oculomics and retinal imaging as the technologies used in this study. Health services delivered outside traditional clinical settings are then introduced, and finally, the section closes with a review of customer acceptance of AI and digital health technologies.

2.1 Artificial intelligence in healthcare

Artificial intelligence (AI) refers to the capability of computer systems to perform tasks that typically require human intelligence, such as recognising patterns, making decisions, and learning from experience (Russell et al., 2022). In healthcare, AI encompasses a broad range of computational methods that analyse medical data to support clinical and operational functions (Ali et al., 2023). The most relevant methodologies in this context include machine learning, deep learning, image processing, and data mining (Ali et al., 2023; Topol, 2019). Machine learning refers to algorithms that learn from data to make predictions or decisions without being specifically programmed for each task (D. Lee & Yoon, 2021). Deep learning is a subset of machine learning that uses multi-layered artificial neural networks to process complex, high-dimensional data, making it particularly effective for analysing unstructured data such as images, audio, and text (Hirani et al., 2024; LeCun et al., 2015).

2.1.1 Applications and benefits of AI in healthcare

AI applications in healthcare span a wide range of clinical and operational functions that benefit clinicians, health systems, and patients. In clinical practice, image interpretation and pattern recognition are the most extensively studied application areas. Deep learning models have been applied to medical imaging across radiology, pathology, dermatology, ophthalmology, gastroenterology, and cardiology, where they have demonstrated performance comparable to or exceeding that of physicians in specific diagnostic tasks (Rajpurkar et al., 2022; Topol, 2019). One of the greatest advantages in this domain is AI's ability to process and analyse large volumes of complex data at speeds that exceed human capacity (Fritsch et al., 2022). AI-driven decision support tools can also help clinicians identify patterns that may not be immediately apparent, potentially reducing diagnostic errors and supporting treatment decisions (Ali et al., 2023). In ophthalmology specifically, AI-assisted diabetic retinopathy screening has also been studied in relation

to cost savings, suggesting potential economic benefits alongside diagnostic ones (Rajpurkar et al., 2022). Robotic surgery represents another area of active development, where AI is being utilised to increase precision and reduce recovery times for patients (Ali et al., 2023; D. Lee & Yoon, 2021). Rather than replacing clinicians, AI is generally positioned as a tool that supports human judgement; most scenarios maintain a human in the loop (Rajpurkar et al., 2022).

At the health system level, deep learning has been applied to predicting clinical outcomes such as hospital readmissions, sepsis, and mortality (Topol, 2019). AI technologies are also supporting hospital operations, including nursing and managerial functions, by automating administrative tasks such as scheduling, documentation, and billing, and in turn reducing the workload of healthcare professionals and freeing up time for direct patient care (Hirani et al., 2024; D. Lee & Yoon, 2021). At the population level, AI may enable more scalable approaches to screening and prevention, allowing health systems to manage risks and allocate resources more effectively (Ali et al., 2023). AI has also been discussed in the context of personalised medicine, where algorithms trained on genomic, clinical, and lifestyle data could allow treatments to be tailored to individual patients (Rajpurkar et al., 2022).

AI-powered telemedicine and remote monitoring tools are extending healthcare delivery to home and community environments, improving accessibility and patient engagement (Hirani et al., 2024). Patient-facing applications include wearables, such as smart watches and rings, and smartphone-based tools for health monitoring and disease management (Topol, 2019), as well as virtual health assistants, mental health support, and patient education (Alowais et al., 2023). Lee and Yoon (2021) further identify patient-facing benefits, including improved patient engagement, reduced medical errors, and increased productivity within healthcare organisations.

Despite considerable research interest, the translation of AI tools into routine clinical practice has remained limited. Rajpurkar et al. (2022) note that relatively few AI tools have been implemented in real-world medical practice, and much of the existing evidence is based on retrospective analyses of existing datasets rather than prospective clinical deployment. This gap between demonstrated technological capability and actual healthcare implementation is a recurring theme in the literature.

2.1.2 Challenges of AI in healthcare

Despite the potential benefits outlined above, the integration of AI into healthcare presents significant challenges. A recurring concern is algorithmic bias: because AI models learn from historical data, they may reproduce or

amplify existing disparities in healthcare if training datasets do not adequately represent diverse patient populations (Obermeyer, 2019; Topol, 2019). For example, Obermeyer (2019) found large racial biases in an algorithm used by the U.S. health system that were due to proxies being used to assess patients' risks. A related issue is the quality and availability of training data in general. Labelled medical datasets are costly to produce, as annotation requires expert input, and models trained on data from a single source may not generalise well to other clinical environments (Alowais et al., 2023; Rajpurkar et al., 2022).

A key challenge is the interpretability of AI systems. For the most part, deep learning models function as "black boxes," producing outputs without providing explanations that clinicians or patients can easily understand or examine (Ali et al., 2023). This can complicate clinical decision-making, particularly in high-stakes clinical situations when understanding the reasoning behind a conclusion matters. This lack of transparency complicates clinical responsibility and may undermine trust among both healthcare professionals and patients. Topol (2019) notes, however, that unexplainability is not unique to AI in medicine, as some already established clinical practices also lack full transparency. The question of who takes accountability also remains unresolved: it is currently unclear whether responsibility for model errors should fall on developers, regulators, distributors, or healthcare providers, even when a model has undergone clinical validation (Rajpurkar et al., 2022). Alowais et al. (2023) also raise the issue of hallucination in generative AI systems, whereby a model may produce plausible but factually incorrect outputs, which is a particular concern in clinical contexts.

Data privacy and security are further considerations. AI systems in healthcare typically require access to large quantities of sensitive patient data, which raises questions about consent, data governance, and the risk of breaches (Ali et al., 2023; Alowais et al., 2023). In Europe, the General Data Protection Regulation (GDPR) sets strict requirements on the handling of personal health data. AI-based medical tools are subject to even more regulatory requirements, as most of them are classified as high-risk systems under the EU AI Act.

Finally, there are practical barriers to adoption at the organisational level. Integrating AI tools into existing clinical workflows requires infrastructure investment, staff training, and change management, all of which can be resource-intensive (Hirani et al., 2024; D. Lee & Yoon, 2021). Lee and Yoon (2021) also highlight what they describe as the AI divide: patients with limited experience with digital technologies may find it difficult to develop the kind of trust with AI systems that supports effective care. Since the patient-clinician relationship is known to influence treatment outcomes, the extent

to which AI-mediated interactions affect that dynamic is worth considering. Clinician resistance, rising from concerns about professional autonomy or unfamiliarity with AI, may also slow uptake (Jussupow et al., 2022).

2.2 Oculomics for systemic disease identification

Oculomics is an emerging field of medical science that uses high-resolution retinal imaging and AI technologies to detect systemic health conditions (Zhu et al., 2025). This section introduces the imaging technologies that make this possible, the concept of oculomics and the biomarkers it relies on, and the specific research on CVD risk assessment from retinal images.

2.2.1 Retinal imaging technologies

The retina is the light-sensitive tissue lining the back of the eye. Retinal imaging encompasses a range of non-invasive techniques for visualising the structures of the eye, including the retina, optic nerve, and surrounding vasculature, that is, blood vessels. The two most widely used techniques in both clinical and optical retail settings are fundus photography and optical coherence tomography. Other imaging techniques include optical coherence tomography angiography (OCTA) and fluorescein angiography which are used more in specialised contexts.

Fundus photography is the most established and widely used retinal imaging technique. It captures two-dimensional colour images of the posterior segment of the eye, including the retina, macula, optic disc, and vasculature using a specialised camera (Ghenciu et al., 2024). It is a well-established and relatively low-cost imaging method that provides a visual record of the retinal surface. Fundus photography is commonly used to detect and monitor conditions such as diabetic retinopathy, age-related macular degeneration and glaucoma. It is widely available in optical retail settings as part of routine eye examinations.

Optical coherence tomography (OCT) provides a more detailed, three-dimensional view of retinal structures. OCT uses light wave interferometry to capture cross-sectional images at a high resolution, allowing clinicians to examine individual retinal layers and their thickness and integrity. OCT is especially valuable for identifying subtle structural changes not yet visible on a fundus photograph, and in diagnosing and monitoring macular degeneration, diabetic macular oedema, glaucoma, as well as retinal detachment. OCT has become increasingly common not only in hospital ophthalmology departments but also in optical retail practices, where it is often offered alongside standard sight tests. For a more comprehensive description of eye diseases and retinal imaging techniques, please see Abràmoff et al. (2010).

Both fundus photography and OCT are non-invasive and generally well tolerated by patients. They require minimal patient preparation, no injections, no radiation exposure, and can be taken in minutes. Recent advances in device design, including automated image capture and AI-assisted quality control (Zapata et al., 2020), have further reduced the technical demands on operators, and supported image capture in settings where specialist ophthalmic expertise may not always be available. The growing availability of these technologies outside specialist hospital environments has expanded the potential for population-level eye health monitoring. However, the volume of imaging data generated has grown considerably, and interpreting these images places increasing demands on trained professionals. As Keane of Moorfields Eye Hospital has noted, the number of eye scans being performed is growing at a pace much faster than human experts are able to interpret them (D. Lee & Yoon, 2021). This gap between image acquisition and interpretation capacity is one of the factors driving interest in AI-assisted analysis of retinal images.

2.2.2 Oculomics: concept and biomarkers

The possibility of using deep learning to identify systemic disease risk factors from retinal images was first demonstrated by Poplin and colleagues (2018). Wagner and colleagues (2020) later coined the term *oculomics* to describe how the analysis of eye structures can reveal information about biological processes occurring elsewhere in the body and provide insights into systemic health and disease. The retina offers a unique opportunity for such analysis because, as Wu and Liu (2023) note, it is the only location in the human body where microvasculature, small blood vessels, can be directly visualised non-invasively and at high resolution. Wagner and colleagues (2020) observe that, because the retinal vasculature shares anatomical and physiological characteristics with the microvasculature of the brain and other organs, systemic pathological changes may manifest as visible changes in retinal structures.

Retinal biomarkers studied in oculomics can be split into two categories: vascular and structural. Zhu and colleagues (2025) describe vascular biomarkers as measurable features of the retinal vessel network, such as vessel calibre, tortuosity, branching angles, and vascular density. Together, these parameters describe the geometry and organisation of the microvasculature, which provides information about its functional and structural health. Structural biomarkers, as described by Wagner and colleagues (2020) and Wu and Liu (2023), are derived from the retinal tissue layers themselves and include measurements such as retinal nerve fibre layer thickness, macular morphology, and the presence of small lesions such as microaneurysms or haemor-

rhages. These features can be extracted from retinal images and examined for patterns associated with specific physiological states or disease processes.

Oculomics can be applied to a range of systemic conditions. Patterson and colleagues (2024) identify neurodegenerative disease, metabolic disease, and cardiovascular disease as three leading chronic disease targets for oculomics research. Neurodegenerative diseases such as Alzheimer's and Parkinson's disease have been extensively studied, as the retina shares a common embryological origin with the brain, meaning that neurodegeneration often produces detectable changes in retinal structure (Patterson et al., 2024). Alongside Patterson (2024), Yao and colleagues (2025) highlight metabolic conditions such as type 2 diabetes as also well-represented in the oculomics literature, given the established links between metabolic dysfunction and retinal vascular changes. Cardiovascular disease has likewise been a major focus and is discussed in detail in the following section. The appeal of oculomics across all these conditions lies in its scalability and low patient burden: retinal imaging is fast, non-invasive, and increasingly standardised, which makes it practical for use beyond specialist clinical environments (Wagner et al., 2020).

Advances in artificial intelligence have significantly extended the potential of oculomics. According to Ghenciu and colleagues (2024) and Yao and colleagues (2025), machine learning and deep learning methods enable automated analysis of large retinal image datasets, and can detect complex, multi-biomarker patterns that would be difficult to identify through manual examination. Zhu and colleagues (2025) further note that large-scale imaging datasets linked with health records have enabled researchers to examine associations between retinal features and systemic health indicators across broad populations, which is accelerating research in the field. Kamalzadeh and colleagues (2025) highlight how these technological developments have increased the feasibility of applying retinal imaging for population-level screening purposes. At the same time, Ghenciu and colleagues (2024) caution that further work is needed to standardise imaging protocols and validate biomarker utility across diverse populations before oculomics approaches can be integrated reliably into routine clinical practice.

2.2.3 AI-based cardiovascular risk prediction via retinal imaging

Cardiovascular diseases (CVDs) refer to a group of disorders affecting the heart and blood vessels and are among the leading causes of mortality worldwide. Common cardiovascular diseases include coronary artery disease (heart disease), myocardial infarction (heart attack) and stroke (World Heart Federation, 2026). These conditions are often linked to underlying processes such as atherosclerosis, vascular inflammation, and microvascular dysfunc-

tion. Barriada and Masip (2022) emphasise that because many cardiovascular diseases develop gradually over time and may remain asymptomatic in early stages, risk prediction and early detection are considered critical components of managing and treating conditions.

Traditional cardiovascular risk assessment typically relies on clinical indicators and patient data such as age, sex, blood pressure, cholesterol levels, smoking status, and diabetes status. These variables are incorporated into widely used risk prediction models such as the Framingham Risk Score or other population-based risk charts. However, such models usually require clinical measurements and laboratory testing, which limit their accessibility in large-scale screening contexts. Li and colleagues (2023) and Barriada and Masip (2022) note that in recent years, advances in AI and medical imaging have enabled the development of alternative risk assessment approaches based on retinal imaging data.

The use of retinal images for cardiovascular risk prediction is based on the observation that the retinal vasculature reflects systemic microvascular health. Changes in retinal vessels may indicate underlying vascular processes associated with cardiovascular disease. Li and colleagues (2023) describe how, while earlier research focused on manually measured retinal parameters, the emergence of deep learning has enabled automated extraction of complex image features that may correlate with cardiovascular risk. Deep learning models, particularly convolutional neural networks, can analyse retinal fundus photographs and identify patterns across large datasets that are difficult to detect through conventional clinical observation.

The first notable study in this field was conducted by Poplin and colleagues (2018), who demonstrated that deep learning algorithms trained on retinal fundus images could predict several cardiovascular risk factors, including age, sex, blood pressure, and smoking status. In addition, the model was able to estimate the risk of major adverse cardiovascular events using retinal images alone. This finding suggested that retinal images contain previously unrecognized biomarkers that can be captured through AI-based analysis. Following this work, numerous studies have explored AI models for predicting cardiovascular risk from retinal images. These models typically use large datasets of retinal fundus photographs and associated clinical data to train neural networks, which are then capable of estimating either individual risk factors or overall cardiovascular risk scores. Li and colleagues (2023) note in their systematic review that most studies in this area employ convolutional neural networks to analyse retinal vasculature, typically aiming to classify individuals into cardiovascular risk categories or predict the likelihood of future events. Recent research has also explored the integration of retinal imaging with other data sources to improve prediction accuracy. Cho and col-

leagues (2023) and Li and colleagues (2023) suggest that multimodal AI models combining retinal image features with traditional clinical risk factors, genetic information, or electronic health record data may improve predictive performance compared with clinical variables alone.

2.3 Health services in non-traditional healthcare settings

Delivering a screening service in an optical retail store raises questions about how health services work outside traditional clinical settings. This section presents examples from other non-traditional settings, considers optical retail as a potential platform for health screening and discusses frameworks for understanding service innovation and value creation in this context.

2.3.1 Retail healthcare and alternative screening settings

Health services are usually delivered through primary care and specialist clinical settings. However, there is a range of alternative settings that embed health services into environments people already visit as part of their daily routines. The concept of opportunistic or low-threshold screening means the delivery of preventive health services in settings where individuals are already present for other purposes, without requiring a prior appointment or clinical referral. The idea is that by lowering the threshold for access, these settings can reach a larger population, including groups that do not proactively seek care through traditional channels.

Community pharmacies are an example of this model. Their dense geographic coverage, extended opening hours, and walk-in accessibility make them frequently visited points of contact in many healthcare systems, with patients visiting pharmacies considerably more often than primary care providers (Tsuyuki et al., 2018). Screening programmes for conditions such as cardiovascular risk, diabetes, and hypertension delivered in pharmacy settings have shown positive user feedback and patient satisfaction (Fonseca et al., 2021; Rohla et al., 2016), suggesting that individuals are receptive to health services delivered outside traditional clinical environments. Retail clinics located within supermarkets in the U.S. operate on a similar basis, typically offering a limited range of services such as vaccinations and monitoring of common conditions. Cardiovascular risk screening has also been piloted in dental settings, illustrating that the model can also extend to alternative healthcare environments (Doughty et al., 2023).

These alternative settings have been associated with several benefits as opposed to traditional care pathways. For instance, in the U.S., care initiated in retail or community settings tends to be less costly than that in physician offices or emergency departments, which potentially lowers financial barriers

to preventive care (B. Y. Lee et al., 2009). These settings have also shown potential for reaching population groups that do not proactively engage with traditional healthcare, as demonstrated by increased vaccination rates among working individuals served through retail clinics (B. Y. Lee et al., 2009).

Despite these advantages, the evidence on quality of care in non-traditional settings is mixed, and further research is needed to understand outcomes across different service types and population groups (Hoff & Prout, 2019). Regulatory considerations present an additional challenge, as the permitted scope of services varies across jurisdictions and providers must navigate protocols around result communication and onward referral. The experience from CVD screening in a dental care setting illustrates this point: while non-traditional professionals can be trained to deliver health interventions, careful protocols are needed to minimise patient confusion and ensure appropriate follow-up (Doughty et al., 2024).

Whether and how individuals engage with health services in these settings depends on a range of factors. The diffusion of health service innovations across these non-traditional settings can be understood through Rogers' (Rogers, 2003) Diffusion of Innovations framework. Rogers identifies five characteristics that influence the adoption of an innovation: relative advantage over existing alternatives, compatibility with the values and routines of potential adopters, simplicity of use, observability of results, and trialability. In retail health screening, this framework suggests that uptake is likely to be higher when services are perceived as genuinely beneficial, easily integrated into existing visit behaviour, and low in perceived effort or risk. In retail health contexts, compatibility is particularly relevant: customers visiting these settings for non-health purposes may find the offer of a health service unexpected, and their willingness to engage is likely shaped by how well the service fits their existing visit behaviour and prior expectations. Factors influencing the use of an application can also be viewed through the Technology Acceptance Model (TAM), originally created to assess the acceptance of technologies. This model is examined in more detail in section 2.4.1.

2.3.2 Optical retail as a health service platform

Optical retail is in a favourable position from which to extend into preventive health screening, due to its scale and existing infrastructure. There are nearly 700 optic retail stores in Finland, and over a million people visit an optician or optometrist each year to have their eyes tested (Näe ry, n.d.). A key advantage of providing healthcare services in an optical retail environment is that it reaches a broad population. This aligns with the *compatibility* characteristic in the Diffusion of Innovations framework (Rogers, 2003) discussed

above: the optical retail setting is a place many people already engage with routinely. It presents an opportunity to access a broader patient population, including those who may not yet have symptoms of chronic disease, are at an earlier stage in the disease course, or may not have recently visited a general medical practitioner or accessed health screening elsewhere.

The existing diagnostic equipment further lowers the barrier to introducing an oculomics-based service. As discussed in section 2.2.1, fundus photography and increasingly OCT imaging are already standard equipment in many optical retail practices. This infrastructure lowers the marginal cost of introducing additional screening modules and reduces the workflow disruption associated with service integration.

The role of the optometrist is key in how the service is delivered, and also where its limits lie. In Finland, optometrists graduate with a limited right to prescribe medication and conduct routine eye examinations. When an examination reveals findings that suggest an underlying disease, the optometrist is required to refer the customer to an ophthalmologist. This referral structure is important for the design of a CVD risk screening service too: any risk findings in an optical retail setting would similarly need to be routed to a professional with the expertise to validate the result and provide next steps, rather than being resolved by the optometrist alone.

Silmäasema, the case company for this thesis, operates a hybrid model combining optical retail with eye-health services. Of its more than 150 locations, over 30 combine retail with ophthalmology services, offering comprehensive eye health care, including eye surgeries and extensive eye examinations (Silmäasema, 2025). This positions Silmäasema not as a pure retailer, but as an organisation that already has clinical capacity, often under the same roof as its retail offering.

2.3.3 Service innovation and value creation in retail health

Understanding how optical retailers can successfully extend into health screening requires a theoretical framework that goes beyond clinical feasibility. Service-Dominant Logic (SDL), developed by Vargo and Lusch (2004), offers a valuable lens for this purpose. SDL represents a shift away from a goods-centred view of economic exchange, where a product is produced and sold, towards a service-centred perspective in which value is always co-created through interactions between providers and customers (Vargo & Lusch, 2004). A central idea in SDL is that value is not defined in a product or service offering by the provider alone but is determined by the customer through use and experience, which Vargo and Lusch (2008) term "value-in-use."

In an optical retail health screening, SDL reframes the service not as a diagnostic product delivered to a passive customer, but as a collaborative process in which both the optical professional and the customer contribute to the creation of health-relevant value. The customer brings their health history, concerns, and engagement; the provider brings expertise, technology, and clinical infrastructure. Value is co-created in the interaction between them: for example, when a customer who was unaware of their cardiovascular risk leaves the encounter with actionable information and a referral pathway. This co-creation dimension can also be viewed through the lens of customer participation: the more a customer perceives themselves as an active contributor to the value being produced, rather than a passive recipient of a diagnostic output, the more readily they are likely to accept the service as relevant to them, and the greater the value they are likely to derive from it. This framing has practical implications for service design: it suggests that the quality of the interaction, the clarity of communication, and the customer's sense of agency and understanding are as important to the value of the service as the technical performance of the health technology.

SDL also highlights the concept of the value proposition, rather than just selling a product (Vargo & Lusch, 2004). For optical retailers, introducing cardiovascular screening represents a repositioning of the value proposition: from a provider of vision correction and eyewear to a trusted partner in broader health management. This repositioning carries strategic implications, including potential for increased customer loyalty, differentiation from competitors, and an expanded role within the local healthcare ecosystem.

From the customer's perspective, the Health Belief Model (Rosenstock, 1974; Rosenstock et al., 1988) provides a complementary lens for understanding engagement with preventive screening. The model proposes that health-related behaviour is influenced by perceived susceptibility to a condition, perceived severity of its consequences, perceived benefits of taking action, perceived barriers to doing so, and self-efficacy. In the context of retail cardiovascular screening, customers who do not consider themselves at risk, or who are uncertain about the value or accuracy of the service, may be less likely to engage, even if the service is conveniently available. This underlines the importance of clear communication about who the screening is for, what it can detect, and what follow-up actions are recommended. Providing a customer with a screening result is not the same as ensuring that the customer understands it. Perceived benefits can only translate into action if customers are told what the result means for them personally and what steps they are expected to take next. This is especially important with regard to AI (Ankolekar, 2026). Together, SDL and the Health Belief Model provide a framework for understanding both the service design and the customer behaviour dimensions of oculomics-based screening in optical retail settings.

2.4 Customer acceptance of AI and digital health technologies

The success of a new service ultimately depends on whether customers are willing to use it. This section reviews theoretical models of technology acceptance, then presents previous empirical findings on patient and consumer attitudes toward AI in healthcare.

2.4.1 Technology acceptance models

Research on the adoption and use of new technologies has long emphasised the importance of understanding the determinants of individual acceptance. Within this field, the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) are among the most widely used theoretical frameworks for explaining users' intentions and behaviours regarding technological systems. TAM was originally developed by Davis (1989) to provide a model of information technology acceptance. TAM is based on three main elements: (a) perceived usefulness, defined as the degree to which an individual believes that using a technology will enhance their performance, (b) perceived ease of use, defined as the degree to which a technology is expected to be effort-free, and (c) external factors which shape usefulness and ease of use rather than acting on behavioural intention directly. These constructs are thought to shape users' attitudes toward a technology and, consequently, their behavioural intentions to use it (Davis, 1989; Schretzlmaier et al., 2022). This third element is particularly relevant to this thesis, as it points toward the kinds of contextual and individual factors, such as prior technology experience, trust, or communication about the screening, that may influence how this specific solution is adopted beyond the two core constructs. TAM is an important model in technology acceptance research, with extensive application across domains including information systems, e-commerce, and healthcare (Ammenwerth, 2019). Figure 1 visualizes the components of the TAM.

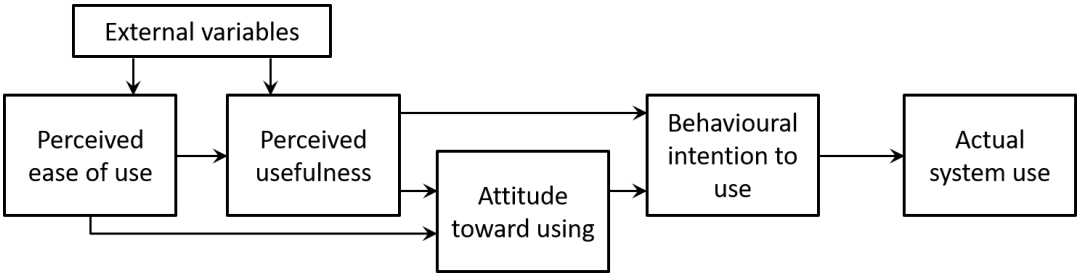

Figure 1. Technology Acceptance Model (TAM). Adapted from Davis (1989)

While TAM provides a focused explanation rooted in individual cognitive perceptions, the Unified Theory of Acceptance and Use of Technology

(UTAUT) offers a broader framework by synthesising elements from eight prominent technology adoption models, including TAM, TRA, and the Theory of Planned Behaviour (TPB) (Venkatesh et al., 2003). UTAUT was developed primarily to explain acceptance and use of technology systems in organisational contexts, and its full model is not a natural fit for a consumer-facing, one-off health screening service of the kind examined in this thesis. Rather than adopting UTAUT in its entirety, this thesis draws selectively on two of its elements that extend TAM's external-factors component: performance expectancy and effort expectancy, which parallel perceived usefulness and perceived ease of use but emphasise the *expectation* of benefit and effort rather than a general belief about the technology, and social influence, which reflects the perceived expectations of significant others regarding technology use (Venkatesh et al., 2003; Ammenwerth, 2019). UTAUT's treatment of demographic moderators (age, gender and experience) is also drawn on here, as these characteristics may help explain variation in how customers in this study respond to the screening service (Venkatesh et al., 2003).

2.4.2 Patient and consumer attitudes toward AI in healthcare

Understanding how patients and consumers perceive AI in healthcare is essential for anticipating the real-world adoption of AI-based services. While the technical performance of AI systems has been extensively studied, the attitudes and acceptance of end users are equally critical in determining the success of its implementation. Research in this area has grown considerably in recent years, drawing on survey studies, qualitative interviews, and systematic reviews conducted across national and clinical environments. A consistent picture has emerged: patients are open to AI in healthcare, but their acceptance is conditional and shaped by a range of individual, contextual, and communicative factors.

Across studies, patients tend to hold nuanced rather than uniformly positive or negative views. Fritsch et al. (2022) surveyed patients in a German hospital setting and found that more than half of respondents rated AI usage positively and expected it to benefit patient care, though the authors caution that this seemingly favourable reception should not be taken at face value, as important conditions and concerns underlie it. Kauttonen et al. (2025), drawing on a large quantitative survey of over 1,000 Finnish participants, similarly found that general attitudes toward AI in healthcare were moderately positive, but that trust and intention to use were contingent on several individual-level factors such as demographics, personality traits and technology-related attributes. Richardson et al. (2022), using a qualitative focus group methodology with primary care patients in the United States, found that patients engaged with AI from multiple frames of reference simultaneously — weighing potential benefits such as improved accuracy and efficiency against concerns

about accountability, equity, and the preservation of the human dimensions of care. These findings are important as they suggest patient attitudes are not simply positive or negative, but contextually reasoned, with the same individual holding both optimism and apprehension depending on the specific application in question.

A particularly consistent finding across the literature is that patients describe acceptable AI as a supportive tool operating under human oversight, rather than as an autonomous decision-making system. Fritsch et al. (2022) found near-unanimous agreement among respondents (over 96%) that a human clinician should retain ultimate responsibility for diagnosis and treatment, even when AI is involved. Richardson et al. (2022) echoed this, finding in focus groups that patients were generally comfortable with AI as a tool to assist clinicians but became considerably more hesitant when AI was framed as making independent or autonomous decisions. Young et al. (2021), in a mixed-methods systematic review, found that this preference for human-in-the-loop AI persisted even when patients were informed that the AI might outperform a human clinician in accuracy.

Research also identifies a range of individual-level factors that shape attitudes. Kauttonen et al. (2025) found that general technology attitudes, prior technology use, and personality traits were the primary drivers of trust and willingness to use AI in healthcare, with the specific clinical use case having less impact than anticipated. This implies that efforts to improve acceptance should be directed at building general technology confidence rather than at communicating the merits of specific AI tools. Shevtsova et al. (2024), whose mixed-methods study examined factors influencing trust and acceptance among healthcare stakeholders across European countries, found that of 19 identified factors, 16 were rated as highly relevant to trust and acceptance, including transparency, explainability, accountability, and physician oversight. Notably, Shevtsova et al. (2024) found that demographic characteristics such as gender, age, and education were rated as comparatively low in relevance by stakeholders, which stands in contrast to Fritsch et al. (2022) and Kauttonen et al. (2025), both of whom found these variables to be meaningful predictors of individual patient attitudes. This divergence may reflect a difference in perspective: Shevtsova et al. (2024) surveyed researchers, technology providers, and policymakers rather than patients directly, which may explain why structural and ethical factors were prioritised over demographic ones.

The nature of the AI application itself also shapes acceptance, particularly in terms of perceived invasiveness and clinical risk. Kauttonen et al. (2025) found that non-invasive monitoring applications were the most widely accepted AI use cases, while applications involving autonomous clinical deci-

sion-making caused more hesitation. Baldus et al. (2026) found that patients place significant value on clear information about an AI device's performance, the degree of clinician oversight, and its regulatory status when deciding whether to engage with it. Baldus et al. (2026) also found that the impact of such informational transparency varied across patient subgroups, pointing to the need for tailored communication strategies. Shevtsova et al. (2024) similarly highlighted transparency and explainability as among the most critical systemic requirements for trust, reinforcing the finding from Fritsch et al. (2022) that data privacy concerns were a significant barrier to acceptance, particularly among less technically confident patients.

A further dimension concerns the role of the healthcare professional in shaping patient attitudes. Baldus (2026) found that most patients indicated they would be more open to AI if a doctor explained the technology and its functioning beforehand. Richardson et al. (2022) similarly emphasised that patients use the clinician relationship as a trust anchor when evaluating new technologies, and that AI tools perceived as disrupting or displacing this relationship were viewed with particular concern. Kauttonen et al. (2025) did not directly measure the clinician effect but found that broader institutional trust — encompassing the healthcare system as a whole — was a significant predictor of AI acceptance, suggesting that organisational credibility may serve as a proxy trust signal when an individual clinician relationship is less established. Shevtsova et al. (2024) reinforced this from a stakeholder perspective, identifying physician oversight and accountability mechanisms as among the highest-priority requirements for AI acceptance across the European healthcare contexts they examined.

Finally, most empirical research in this area has focused on applications in clinical or hospital settings. Evidence on how attitudes may differ when AI-based health services are delivered in non-clinical or retail environments remains limited. The findings reviewed here nonetheless suggest that perceived professionalism, transparency, human oversight, and data privacy are likely to be equally if not more important in retail contexts, where patients may enter with weaker a prior trust in the provider and less familiarity with the governance of health data. Richardson et al. (2022) note that patients draw on multiple evaluative frameworks simultaneously when assessing healthcare AI, including prior experiences with illness, values, and social context, implying that the setting in which a service is delivered is not a neutral backdrop but an active component of how trust is formed and maintained.

3 Research material and methods

This section describes the research design and methods used to answer the research questions.

3.1 Research Design

This thesis investigates customer perceptions of AI-based cardiovascular risk screening in an optical retail setting and the factors that influence acceptance of such a service. A quantitative, cross-sectional research design was adopted to explore customer attitudes toward an AI-based CVD risk assessment service in optical retail settings. A survey-based approach was considered appropriate because the primary interest of this study lies not in an in-depth understanding of individual experiences, but in how a new service is received and adopted across a broad and heterogeneous customer base. Understanding the potential reception and adoption of an AI-based screening service at scale requires data from a sizeable and varied group of respondents, which a quantitative survey design is well-suited to provide, compared with methods that yield richer but more limited insight from fewer participants.

Data were collected through an anonymous questionnaire administered to customers participating in a pilot project at Silmäasema, a Finnish optical retail chain. A cross-sectional design was appropriate given the exploratory nature of the study and the practical constraints of a real-world pilot setting, where data collection was tied to a limited pilot period rather than a longitudinal follow-up.

The study follows an abductive logic overall: established theoretical frameworks, such as the Technology Acceptance Model, and previous studies provided an initial set of relevant constructs, which were then refined through discussions with business and medical professionals at the case company to fit the specific service context. Given the comparatively modest sample size of this study (N = 184) relative to studies such as Kauttonen et al.'s (N = 1100), the statistical analysis as a whole is treated as exploratory rather than confirmatory: findings are used to identify patterns and generate explanations warranting further study, rather than to confirm or reject pre-registered hypotheses at scale.

3.2 Data Collection

This section describes how data were collected: first, the research context and how the sample group was gathered, then how the questionnaire was developed and delivered.

3.2.1 Research context and participant recruitment

The empirical data for this thesis were gathered as part of a pilot project conducted by Silmäasema, a Finnish optical retail and eye health care company. The pilot was carried out at a store in the Helsinki Metropolitan area during March and April 2026. The pilot aimed to evaluate the use of a digital fundus camera together with an AI platform for assessing cardiovascular disease risk from retinal fundus images. The AI platform analyses fundus images for indicators of major cardiovascular risk factors, including hypertension and high cholesterol. Participants were invited to participate in the pilot and received fundus photographs and OCT scans, as well as an estimate of their cardiovascular disease risk, free of charge.

Participants were recruited from the existing customer bases of two Silmäasema stores in the Helsinki Metropolitan area. Customers who had provided contact information and had consented to marketing communications were sent an email invitation to participate in the pilot. Invitations were sent between February and March 2026, followed by text message reminders. Additional recruitment was carried out through phone calls and flyer distribution at the shopping mall where the store is located. The pilot was also advertised at the store and customers visiting the store for other appointments were told about the pilot and possibility of participating.

Eligibility criteria for participation in the screening were defined by the AI platform provider and included: age between 40 and 70 years, no previous heart attack or stroke, no prior vascular surgery, no current cholesterol medication, no previous diagnosis of retinal disease, myopia no greater than -6 dioptres, no visual impairment, and not being pregnant. In total, 282 individuals took part in the pilot screening service.

Survey respondents were drawn from this pool of participants. Almost all participants were asked to complete the survey. In cases where time was limited or where a language barrier was present, the survey was skipped. This resulted in 184 survey responses, which form the dataset analysed in this thesis.

Participants provided written informed consent prior to taking part in both the pilot project and the survey. The study follows the tenets of the Declaration of Helsinki for medical research involving human subjects (WMA, 2013). Survey responses were collected anonymously and were not linked to participants' health data. Access to the survey responses was limited to two representatives of the case company and the author.

3.2.2 Questionnaire development and administration

The survey aimed to measure customer attitudes toward AI-assisted health services and toward preventive health screening in an optical retail setting. Relevant constructs and items for the questionnaire were identified during the literature review.

The components measuring attitudes toward AI were largely based on the study by Kauttonen et al. (2025), which examined trust and acceptance of AI across several healthcare applications. Their study also used predominantly Likert-scale items. Statements on the current state of healthcare services, attitudes toward new technologies, and general AI attitudes and knowledge were adapted from their questionnaire, along with the specific constructs used to assess opinion of the AI application: trust, explanation of results, training data, developer, and data use. Additional items were selected from the questionnaires used by Baldus et al. (2026) and Fritsch et al. (2022).

Most items measuring customer acceptance of preventive health screening in a retail setting were developed specifically for this study, informed by the Technology Acceptance Model. These items were designed to capture how useful customers considered the service to be, their intention to use it, the perceived appropriateness of the setting and ease of use, and their understanding of the service. To supplement and validate the literature-based item selection, discussions with business and medical professionals at the case company were held to identify which constructs and items were most relevant to the specific service context. Table 1 summarizes the structure of the questionnaire and the sources informing each section.

The questionnaire was pretested with eight internal stakeholders at the case company. Based on their feedback, the wording of several questions was simplified to be more accessible to a general audience, and some items were removed. The pretesting also provided an estimate of a completion time of around 10 minutes, which was communicated to participants in the introduction of the questionnaire.

The final questionnaire consisted of three sections. The first section collected background information, including demographic characteristics, health background, and measures of the respondent's experience with and knowledge of technology. The second section measured perceptions of AI in the health service context using a 5-point Likert scale (strongly disagree, disagree, neither disagree nor agree, agree, strongly agree). Statements were formulated both positively and negatively. The third section, using the same Likert scale, assessed attitudes towards a preventive health screening service in this new setting. A free-text field was included at the end to allow partici-

pants to provide open comments. A total of 56 questions were included in the final questionnaire. All questions except the final open comment question were mandatory. The questionnaire was administered in Finnish. The full questionnaire in Finnish and English are provided in Appendices A.1 and A.2.

Table 1: Questionnaire structure and sources

Section	Number of questions	Source
1. Background		
Demographic characteristics	3	Adapted from Kauttonen et al., 2025
Health background	5	Adapted from Kauttonen et al., 2025; Fritsch et al., 2022; self-developed
Technology background	12	Adapted from Kauttonen et al., 2025; Fritsch et al., 2022 and Baldus et al., 2026
Reasons for participation	1	Self-developed
2. Attitude toward AI application		
General trust	3	Adapted from Kauttonen et al., 2025
Trust in AI application	6	Adapted from Kauttonen et al., 2025, self-developed
Explainability of results	3	Kauttonen et al., 2025
Training data	2	Kauttonen et al., 2025
Developer	3	Kauttonen et al., 2025
Privacy	2	Adapted from Kauttonen et al., 2025
3. Perception of the service	16	Self-developed, adapted from Kauttonen et al., 2025; Fritsch et al., 2022

The questionnaire was hosted on the Webropol platform. Participants completed the survey on a tablet provided on-site in the waiting room before their imaging appointment for the pilot. Data collection took place over 14 days from March to April 2026. A researcher was present throughout data collection to answer any questions about the survey items.

3.3 Data Analysis

Analytical approaches, including data preprocessing, construction of composite scores, correlation analysis and regression models are described in this section.

3.3.1 Preprocessing

The dataset was first examined for missing values. To ensure data quality, response patterns were also manually inspected to identify participants who may not have been paying attention while completing the survey. Specifically, the variability of responses was assessed to identify cases where respondents may have selected the same response option throughout the questionnaire without reading the statements.

Prior to analysis, ordinal responses were converted into numerical values (e.g., *very poor* = 1 to *very good* = 5; *strongly disagree* = 1 to *strongly agree* = 5 for Likert-scale items). Negatively worded items were reverse-scored so that higher values consistently represented stronger agreement for each item. Reverse scoring was performed by subtracting the original Likert-scale response (1–5) from six.

Two categorical variables were recoded to reduce the number of small subgroups. Education level, which was originally recorded in seven categories, was collapsed into four categories (basic education, high school or vocational college, undergraduate, and graduate) to avoid excessively small groups given the sample size (N = 184). Eight respondents who selected the "Other"-option for their education level were manually assigned to the appropriate category based on their free-text responses. Prior cardiovascular risk assessment was recoded into a binary yes/no variable rather than distinguishing between different assessment methods. All subsequent analyses were conducted using RStudio. The survey questions, response options, and corresponding variables are presented in Appendix A.3.

3.3.2 Composite scores

Composite scores were created for each factor construct: three constructs from the background section (technology attitude, AI knowledge, AI attitude), seven from the AI-trust section (general trust in AI in healthcare, trust in the AI application, human oversight trust, explainability, training data, developer, and privacy), and five from the service-evaluation section (usefulness, understanding, appropriateness of setting, data safety, and intention). See Appendix A.3 for survey items and how they were combined to form factor constructs.

Composite scores were calculated as the unweighted arithmetic mean of their constituent items on the original 1–5 Likert scale. This approach was chosen over the confirmatory factor analysis (CFA) approach used by Kauttonen et al. (2025), who derived weighted factor scores using the lavaan package in R with maximum likelihood estimation on a sample of 1100 respondents. Given

the more modest sample size of this study (N = 184), a simple composite approach was considered more appropriate, as CFA estimates become unstable when the ratio of observations to estimated parameters is low (Brown, 2015).

Internal consistency of each composite was assessed using Cronbach's alpha, with $\alpha \geq .70$ used as the conventional threshold for acceptable reliability (Nunnally & Bernstein, 1994). Constructs falling below this threshold were reviewed individually. If low alpha appeared attributable to ceiling effects rather than a genuinely incoherent construct, a Spearman rank correlation between the constituent items was additionally examined as a robustness check, since Pearson-based statistics such as Cronbach's alpha can understate reliability when items are strongly skewed (Spearman, 1961).

3.3.3 Descriptive, subgroup, and correlation analysis

Item- and construct-level descriptive statistics (means, standard deviations, skewness, and kurtosis) were calculated for all survey items and composite scores. This served two purposes: to characterise the sample's overall responses prior to the more detailed analyses, and to assess the distributional assumptions required for selecting appropriate statistical tests. Several items exhibited skewed distributions, with responses clustered towards the agreement end of the scale. Based on these findings, non-parametric methods were selected for the subgroup and correlation analyses described below.

Subgroup analyses were conducted to examine whether customer perceptions differed according to demographic and health-related characteristics (age, gender, education level, prior CVD risk assessment, and wearable technology use). Standard guidance states that rank-based tests are preferable to parametric alternatives (e.g., t-tests, ANOVA) for ordinal or non-normally distributed data of this kind. Given the skewed and ordinal nature of the data, Mann-Whitney U tests (Wilcoxon rank-sum tests) were used for two-group comparisons (gender, prior CVD risk assessment, wearable technology use), whereas Kruskal-Wallis tests were used for comparisons involving three or more groups (age group and education level). For the Mann–Whitney U tests, the effect size r was calculated and interpreted using Cohen's (1977) guidelines, where values of .10-.29 indicate a small effect, .30-.49 a moderate effect, and ≥ .50 a large effect. For the Kruskal-Wallis tests, epsilon-squared (ε^2) was reported as the measure of effect size and interpreted using conventional benchmarks of approximately .01 (small), .06 (medium), and .14 (large), adapted from Cohen (1977). Statistical significance was defined as $p < .05$.

Spearman's rank correlation coefficients were calculated between individual variables and composite scores to examine the relationships between con-

structs and to assess the potential presence of multicollinearity prior to the regression analyses. Spearman's correlation was selected instead of Pearson's correlation because it is appropriate for ordinal data and provides a more robust estimate of association when variables are not normally distributed. Correlations were considered strong at $\rho \geq .5$, moderate at $.3 \leq \rho < .5$, with statistical significance defined as $p < .05$ (Cohen, 1977).

3.3.4 Regression analysis

Multiple linear regression analyses were conducted to examine the influence of demographic characteristics, health background, and technology-related constructs on the acceptance of the AI application. Following the approach of Kauttonen et al. (2025), a parallel-outcomes regression design was adopted. Rather than modelling attitudinal constructs as predictors of one another (e.g. using trust to predict intention), the same set of predictor variables was entered into separate regression models for each outcome construct.

For each outcome, two ordinary least squares (OLS) regression models were first fitted. The first model included demographic and health-related variables, whereas the full model additionally included technology-related constructs. The incremental contribution of the additional predictors was evaluated by comparing the nested models using an F-test. Variance inflation factors (VIFs) were calculated to assess multicollinearity among the predictors, with VIF values below 5 indicating no evidence of problematic multicollinearity.

Model performance was assessed using the adjusted coefficient of determination (adjusted R^2), which accounts for the number of predictors included in the model. Statistical significance was defined as $p < .05$.

For models demonstrating sufficient explanatory power, standardised regression coefficients (β) were additionally calculated. This allowed the comparisons of the relative importance of predictors measured on different scales, as unstandardised coefficients are not directly comparable across variables with different units or ranges. Model diagnostics, including residual plots and Cook's distance, were examined for selected models.

A quadratic term for AI knowledge was included to test a finding reported by Kauttonen et al. (2025), who observed an inverted U-shaped relationship between self-reported AI knowledge and trust- and acceptance-related outcomes. Specifically, both the least and the most knowledgeable respondents expressed less favourable attitudes, consistent with a Dunning–Kruger-type pattern and AI divide mentioned by Lee and Yoon (2021). Because a variable

and its squared term are typically highly correlated when calculated from the original 1–5 scale, AI knowledge was mean-centred before calculating the quadratic term. Mean-centring reduced the VIF of the linear and quadratic AI knowledge terms without affecting the estimated quadratic coefficient, its standard error, or its *p*-value.

4 Results

This section presents the survey findings. It begins with the characteristics of the sample, followed by the reliability of composite constructs used in the analysis, subgroup comparisons across demographic and health-related variables, and finally correlation and regression analyses to examine factors associated with customer acceptance.

4.1 Sample characteristics

4.1.1 Respondent demographics, health and technology background

A total of 184 participants completed the questionnaire. As all survey questions except the final open-ended comment were mandatory, the dataset contained no missing values. To assess response quality, response patterns were examined for evidence of inattentive responding. No respondent selected the same response option for every Likert-scale item, suggesting that all participants engaged with the questionnaire. Consequently, all 184 responses were retained for analysis. Survey data were exported from the Webropol platform and imported into RStudio for statistical analysis. A full table of descriptive statistics for all questionnaire items is included in Appendix A.4.

The demographic characteristics of the respondents are presented in Table 2. The sample consisted predominantly of older adults, with 42.9% of participants aged 60-70 years and 36.4% aged 50-59 years. Women comprised 72.8% of the sample. Overall, the respondents were relatively well educated, with 61.5% holding an undergraduate or graduate degree.

Table 2: Demographic characteristics of respondents

Variable	Value
Age (%) [*n*]	
• 40-49	20.7 [38]
• 50-59	36.4 [67]
• 60-70	42.9 [79]
Gender (%) [*n*]	
• Female	72.8 [134]
• Male	27.2 [50]
Highest level of education (%)	
• Basic education	6.0
• High school or vocational college	32.6
• Undergraduate (e.g. Bachelor)	33.2
• Graduate (e.g. master's)	28.3

Most respondents reported relatively good health and little use of healthcare services. The majority (83%) had visited healthcare services only a few times or not at all during the previous 12 months, and the same proportion rated their overall health as good or very good. Opinions regarding the current state of healthcare services were more varied: 46% of respondents were satisfied, 25% were neutral, and 28% were dissatisfied. In addition, 75% reported that they had never previously undergone cardiovascular disease risk assessment.

Participants were motivated primarily by health awareness rather than convenience. The most frequently selected reasons were a desire to learn about their own CVD risk (85%), an interest in preventive healthcare (80%), supporting research (80%), and obtaining retinal imaging (75%). Cost-free access to the assessment (67%) and curiosity about artificial intelligence (58%) were also frequently selected. Only 32% of participants selected the convenience of doing it alongside an eye exam as their motivation.

Overall, respondents reported a relatively high level of technology affinity. Only 3% rated their information technology (IT) skills as below average, while 64% reported following developments in new technologies and 86% described themselves as willing to adopt new technologies. Awareness of artificial intelligence was widespread: 97% of respondents had heard of or read about AI, and 71% reported having previously used AI applications.

4.1.2 Attitude on AI application

Attitudes towards the AI application were assessed using five-point Likert-scale items ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). Perceptions of AI were measured across five themes: trust, explainability, training data, manufacturer, and data privacy, which were later combined into constructs. The distributions of responses to the individual statements are presented in Figure 2.

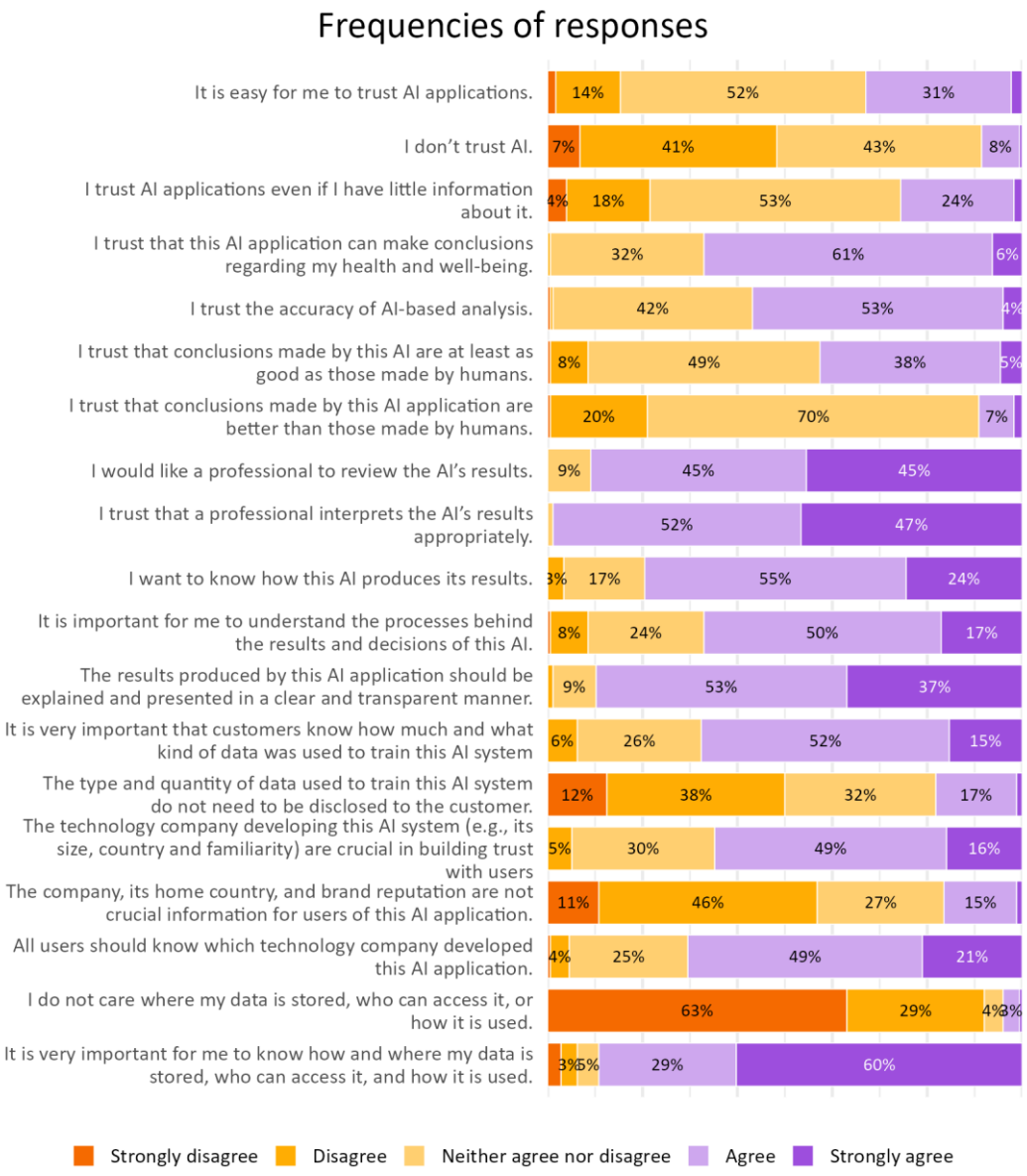

Figure 2. Distribution of responses to statements on AI attitude

Overall, respondents expressed moderately positive attitudes towards AI in healthcare, although responses varied across the trust-related items. Approximately one-third of respondents (33%) agreed that they found it easy to trust AI, while 26% agreed that they could trust AI despite having limited knowledge of it. For both statements, however, just over half of respondents (52% and 53%, respectively) selected the neutral response option.

Trust in the specific AI application used in the pilot, CVD risk assessment from retinal images, was more positive. Approximately 68% of respondents trusted the AI to draw conclusions about their health, while only 1% disagreed that they trusted the accuracy of the AI analysis. At the same time, re-

spondents clearly valued human oversight in the use of AI: 91% want a professional to review the AI results, and 99% trust that a professional will interpret the results correctly.

Explainability-related questions received the highest levels of agreement among the measured items. 89% agreed that results should be presented clearly and transparently, 80% wanted to know how the AI generates its outputs, and 67% considered it important to understand the processes behind the AI's decisions.

Participants also considered information about the AI system itself to be important. 66% agreed that customers should be informed about the amount and type of data used to train the AI model. In addition, over half regarded the identity, size, reputation, and country of origin of the AI developer as important factors influencing their trust in the application.

Respondents expressed particularly strong views regarding the handling of personal data. Nearly nine in ten participants (89%) considered it very important to know how and where their personal data waw stored, who had access to it, and how it would be used. In contrast, only 4% indicated that this information was unimportant. This item received the highest level of agreement of any statement included in the questionnaire.

4.1.3 Customer perception of service

The latter part of the questionnaire assessed participants' perceptions of the preventive CVD screening service offered in an optical retail setting. Figure 3 presents the distribution of responses to these statements.

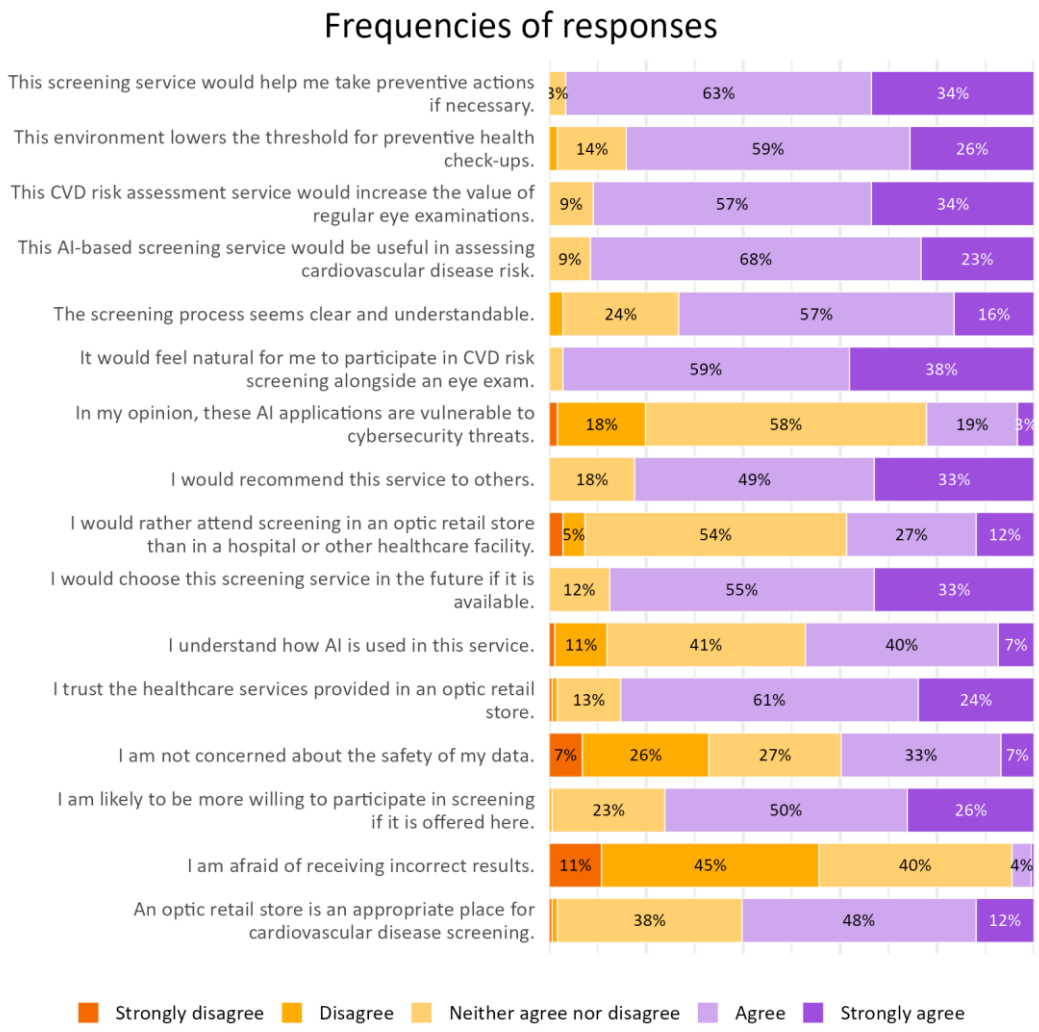

Figure 3. Distribution of responses to statements on service perception

Attitudes toward the service itself were broadly positive. 91% viewed it as useful for CVD risk assessment, 97% felt it would help them take preventive action if needed, and 92% agreed it would add value to a regular eye exam. The statement that it would feel natural to combine CVD screening with an eye examination received the highest level of agreement within this section (97%), indicating that respondents generally perceived the two services as a good fit.

Understanding of the role of AI within the service was less positive. While 74% agreed that the screening process appeared clear and understandable, fewer than half (48%) agreed that they understood how AI specifically is used within it.

Attitudes towards providing preventive health services in an optical retail setting were generally favourable. Most respondents (86%) reported trusting

health services offered in an optical retail store, and 84% agreed that the setting lowers the threshold for preventive health checks. However, only 39% would actively prefer an optician over a hospital or other health facility for CVD screening, with 53% remaining neutral.

Behavioural intention toward the service was strong. Of the participants, 87% indicated that they would choose this service if it were available in the future, and 83% would recommend it to others.

4.2 Construct reliability and composite scores

Internal consistency was assessed for each construct using Cronbach's alpha (Table 3). Eleven of the fifteen constructs demonstrated acceptable internal consistency ($\alpha \geq .71$). Four constructs (AI attitude, data safety, human trust, and privacy) exhibited lower reliability and were examined in greater detail.

The AI attitude construct initially showed slightly lower than acceptable internal consistency ($\alpha = .68$). Examination of the individual items revealed *"With AI, anything is possible"* (AI_attitude_2) as an outlier. Compared with the remaining items, which focused on the practical benefits of AI, this statement reflected a more general and optimistic view of AI. Removing the item increased Cronbach's alpha to .73. Therefore, the final composite score only included three items.

The two-item data safety construct demonstrated poor internal consistency ($\alpha = .20$). Inspection of the items indicated that they addressed different concepts: one measured concern about the safety of personal data, whereas the other assessed perceived vulnerability of AI applications to cybersecurity threats. As these items did not appear to measure a common underlying construct, no composite score was created, and the items were analysed separately where relevant.

The two items measuring trust in human oversight also showed lower than acceptable internal consistency ($\alpha = .55$). Both items exhibited pronounced ceiling effects, with mean scores above 4.3 on the five-point scale, indicating limited response variability. Given the combination of low internal consistency and restricted variance, this construct was excluded from the regression analyses.

The privacy construct fell below the conventional threshold ($\alpha = .59$). However, Spearman's rank correlation indicated a substantial positive association between the two items ($\rho = .65$, $p < .001$). This suggests that the low Cronbach's alpha may be due to ceiling effects rather than an absence of a

common underlying construct. The composite score was therefore retained for the subsequent analyses, with this limitation acknowledged.

Table 3: Descriptive statistics and internal consistency of final composite scores

Construct	Mean	Standard deviation	Cronbach's alpha α
Technology attitude	3.545	0.77	0.79
AI knowledge	3.966	0.66	0.71
AI attitude (AI_attitude_2 dropped)	3.775	0.62	0.73
Healthcare AI trust	3.236	0.62	0.74
Trust	3.4	0.47	0.74
Explainability	4	0.64	0.81
Training data	3.6	0.76	0.71
Developer	3.7	0.69	0.76
Privacy	4.4	0.72	0.59
Usefulness	4.2	0.47	0.78
Understand	3.6	0.67	0.72
Appropriateness of setting	3.9	0.48	0.77
Intention	4.2	0.62	0.81

The four primary outcome constructs used throughout the remainder of this chapter (trust, intention, appropriateness of the setting, and usefulness) all showed acceptable reliability (α = .74-.81) and were retained without modification. These four constructs serve as the main indicators of customers' attitude toward, and perceived value of, the service.

4.3 Subgroup comparisons

Construct scores were compared across five demographic and health-related subgroup variables (age group, gender, education level, prior CVD risk assessment, and wearable technology use) to examine whether participants' perceptions of the AI-based screening service varied systematically across respondent characteristics.

Across four of the five subgroup variables (age group, gender, education level, and prior CVD risk assessment), no statistically significant differences were observed for the outcome constructs on acceptance of the AI application and service perception. Differences were identified in participants' general technology and AI disposition rather than in their evaluation of the screening service itself. Table 4 describes the outcomes with significant differences ($p < .05$) within subgroups. Wearable technology use was the only subgroup var-

iable associated with significant differences in the primary outcome constructs.

Gender

Mann-Whitney U tests showed no significant differences between women (n = 134) and men (n = 50) for any of the primary outcome constructs or other service-evaluation measures. However, men reported significantly higher scores for technology attitude, AI attitude, AI experience, AI knowledge, and self-rated IT skills. Effect sizes were predominantly small, with a moderate effect observed for technology attitude.

Table 4. Significant demographic subgroup differences

Subgroup	Outcome	Statistic *U*	*p*-value	Effect size *r*
Gender	Technology attitude	1860.0	0.000	0.345
	AI attitude	2452.5	0.004	0.210
	AI experience	2586.0	0.012	0.185
	AI knowledge	2586.5	0.016	0.177
	IT skills	2756.0	0.048	0.146
	Outcome	**Statistic H**	***p*-value**	**Effect size ε^2**
Age group	AI experience	16.049	0.000	0.078
	AI knowledge	13.219	0.001	0.062
	IT skills	12.467	0.002	0.058
	Technology attitude	9.505	0.009	0.041
	Outcome	**Statistic H**	***p*-value**	**Effect size ε^2**
Education	IT skills	21.932	0.000	0.105
	AI experience	20.431	0.000	0.097
	AI knowledge	17.455	0.001	0.080
	AI attitude	16.962	0.001	0.078
	Technology attitude	9.264	0.026	0.035

Age group

Kruskal-Wallis tests showed no significant differences across the three age groups (40–49, 50–59, 60–70 years) for any of the four primary outcome constructs or the remaining service-evaluation constructs (all $p > 0.25$). Significant differences were observed for four technology-related constructs. Younger participants reported higher AI experience, AI, self-rated IT skills and technology attitude. Effect sizes ranged from small to moderate.

Education level

Education level differences closely resembled those observed for gender. No significant differences emerged for any outcome construct. However, differences were found in the same technology-related constructs as with gender. Higher education levels were associated with significantly higher scores for

self-rated IT skills, AI experience, AI knowledge, AI attitude, and technology attitude. Effect sizes ranged from small to moderate.

Prior CVD risk assessment

No statistically significant differences were observed between participants who had previously undergone a CVD risk assessment (n = 46) and those who had not (n = 138). Technology attitude approached statistical significance (U = 3781.5, p = .050, r = .15), as did general trust in AI in healthcare (U = 3762.0, p = .055, r = .14); however, neither reached the predefined significance threshold. None of the outcome constructs differed significantly between the two groups.

Wearable technology use

This subgroup comparison broke the pattern observed for the other four grouping variables. Participants who used a wearable device (n = 86) reported significantly higher scores not only for technology attitude, AI knowledge, AI experience, self-rated IT skills, and AI attitude, but also for all four primary outcome constructs: usefulness, appropriateness of the setting, intention to use, and trust in the AI application. All observed effect sizes were small, except for technology attitude, which showed a moderate effect. Results of the subgroup comparison and significant outcomes ($p < .05$) can be found below in Table 5. Full results of subgroup comparisons in Appendix A.5.

Table 5. Significant wearable technology subgroup differences

Outcome	Statistic U	*p*-value	Effect size *r*
Technology attitude	5674.0	0.000	0.301
AI knowledge	5301.5	0.002	0.225
AI experience	5140.5	0.007	0.200
Usefulness	5088.0	0.010	0.189
Appropriate setting	5002.0	0.028	0.162
IT skills	4921.0	0.036	0.155
Intention	4921.5	0.037	0.154
AI attitude	4946.0	0.039	0.152
Trust	4934.5	0.042	0.150

Overall, subgroup analyses showed that demographic characteristics were primarily associated with differences in general technology- and AI-related disposition, whereas evaluations of the AI-based screening service itself were largely consistent across demographic groups. Wearable technology use was the only participant characteristic associated with more positive perceptions of the service across all four primary outcome constructs.

4.4 Correlation analysis

Spearman's rank correlations were calculated between all composite construct scores to examine the relationships between the study variables and to assess potential multicollinearity prior to the regression analyses. The full correlation matrix is presented in Appendix A.6.
Table 6 summarises construct pairs showing strong significant correlations ($|\rho| \geq .50$, $p < .001$).

Table 6. Construct pairs with strong correlations

Cluster	Construct 1	Construct 2	ρ	p
Technology / AI disposition	AI knowledge	AI experience	0.63	< 0.001
	Technology attitude	AI attitude	0.55	< 0.001
	IT skills	AI knowledge	0.54	< 0.001
	IT skills	Technology attitude	0.51	< 0.001
Service-evaluation	Appropriateness of setting	Understand	0.50	< 0.001
	Appropriateness of setting	Intention	0.69	< 0.001
	Usefulness	Understand	0.52	< 0.001
	Usefulness	Appropriateness of setting	0.64	< 0.001
	Usefulness	Intention	0.64	< 0.001
Trust	Healthcare AI trust	Trust	0.53	< 0.001

The strongest correlations fell into two groups. The first consisted of technology- and AI-related constructs, including AI knowledge and AI experience ($\rho = .63$), technology attitude and AI attitude ($\rho = .55$), and IT skills with both AI knowledge ($\rho = .54$), and IT skills and technology attitude ($\rho = .51$). Technology attitude and AI knowledge also showed a moderate positive correlation ($\rho = .49$).

A second, separate, service-evaluation cluster was found, which linked appropriateness of setting, usefulness, understanding, and behavioural intention. Appropriateness of setting and intention showed the strongest pairwise correlation in the entire dataset ($\rho = .69$). Appropriateness of the setting was also correlated with understanding of the service ($\rho = .50$) and perceived usefulness ($\rho = .64$). Usefulness was also strongly associated with intention to use ($\rho = .64$) and understanding ($\rho = .52$).

The third cluster had weaker correlations (.40<ρ <.45), but connected the constructs measuring attitude towards AI application. Explainability had a correlation of .41 with both training data and developer, and training data and developer had a correlation of .43.

Trust in the AI application showed its strongest association with general trust in AI in healthcare (ρ = .53). Moderate positive correlations were also observed with AI attitude (ρ = .49), technology attitude (ρ = .38), understanding of the service (ρ = .37), appropriateness of the setting (ρ = .34), and intention to use (ρ = .34), indicating that trust in the specific application was related to both general AI disposition and perceptions of the screening service.

4.5 Regression analysis

Multiple linear regression analyses were conducted to examine how demographic characteristics, health background, and technology-related variables explained variation in participants' perceptions of the AI-based screening service. For each outcome construct, a core model including demographic and health-related variables was first estimated, followed by a full model that additionally included technology-related items.

A hierarchical F-test was used to test whether the technology-related constructs (technology attitude, AI knowledge, IT skills, AI attitude, and general trust in AI in healthcare) explained significant additional variance beyond the core model of demographics and health context alone (Table 7). Note that the predictors selected here differ slightly from those used by Kauttonen et al. (2025). In their study, general trust in AI in healthcare is treated as an outcome variable rather than a predictor. It is included here as a predictor because this study is concerned with whether general attitude toward AI shapes the evaluation of this specific service. Models were run with both sets of predictors. Comparisons between the nested models demonstrated that adding the technology- and AI-related variables significantly improved model fit for the primary outcome constructs, indicating that these variables explained additional variance beyond demographic and health-related characteristics.

Table 7. Comparing core and full set of predictors

Outcome	F (18,165)	*p*-value	Technology variables add significant value?
Trust	12.23	< 0.001	Yes
Intention	5.12	< 0.001	Yes
Appropriateness of setting	3.03	0.003	Yes
Usefulness	2.61	0.01	Yes
Explainability	2.7	0.008	Yes
Training data	1.06	0.3	No
Developer	1.77	0.08	Marginal
Privacy	2.18	0.03	Yes
Understand	2.88	0.005	Yes
Accuracy	1.78	0.08	Marginal
Data safety 1	0.94	0.49	No
Data safety 2	1.45	0.18	No

Variance inflation factors were below 2, suggesting that multicollinearity was not a concern despite the inclusion of several related technology constructs.

Table 8 summarizes model fit for the full model of each of the outcomes. Five models reached statistical significance: trust in the AI application, behavioural intention, appropriateness of the setting, usefulness and understanding of the service. Interestingly, these include the four primary outcome constructs mentioned in 4.2. The models predicting the remaining constructs showed comparatively weak explanatory power.

Table 8: Model fit summary for full regression model of each outcome

Outcome	**R^2**	**Adj. R^2**	**F(18,165)**	**p-value**
Trust	0.419	0.355	6.6	< 0.001
Intention	0.235	0.151	2.82	< 0.001
Appropriateness of setting	0.168	0.077	1.85	0.024
Usefulness	0.187	0.099	2.11	0.007
Understand	0.183	0.094	2.06	0.009
Explainability	0.138	0.044	1.47	0.106
Training data	0.09	-0.009	0.906	0.572
Developer	0.125	0.029	1.3	0.191
Privacy	0.136	0.042	1.44	0.118
Accuracy	0.137	0.043	1.46	0.113

Data safety 1	0.078	-0.022	0.7766	0.725
Data safety 2	0.086	-0.014	0.861	0.626

Trust in the AI application was the best-explained outcome (adjusted R^2 = .355, p < .001). General trust in AI in healthcare was the strongest predictor (b = 0.258, β = .343, p < .001), followed by AI attitude (b = 0.181, β = .240, p = .005). AI knowledge (b = 0.111, β = .156, p = .086) and technology attitude (b = 0.094, β = .154, p = .085) both showed marginal positive associations with trust in the AI application. None of the demographic or health-related variables reached statistical significance in the final model.

Behavioural intention was also predicted significantly by the full model (adjusted R^2 = .151, p < .001). Technology attitude was the strongest predictor (b = 0.299, β = .375, p < .001), while general trust in AI in healthcare also made a significant positive contribution (b = 0.170, β = .172, p = .039). Gender was the only demographic variable associated with behavioural intention, with men reporting lower intention to use the service than women after controlling for the remaining predictors (b = -0.267, β = -.193, p = .013). AI knowledge was not a significant predictor of behavioural intention (b = -0.141, β = -.150, p = .148).

The model predicting perceived appropriateness of the optical retail setting explained a modest proportion of the variance (adjusted R^2 = .077, p = .024). General trust in AI in healthcare was the only statistically significant predictor (b = 0.161, β = .207, p = .018). None of the remaining demographic, health-related, or technology-related variables reached statistical significance.

The regression model for perceived usefulness was statistically significant overall (adjusted R^2 = .099, p = .007), although no individual predictor reached the conventional level of statistical significance. Wearable technology use (p = .063), gender (p = .074), technology attitude (p = .079), and satisfaction with current healthcare services (p = .085) showed marginal associations with perceived usefulness.

Understanding of the service had a significant model (adjusted R^2 = .094, p = .009). Health status was the strongest significant predictor (b = 0.3, β = .165, p = .043). Respondents who estimated their health to be good or very good understood the service better than those with neutral or poor health. General trust in AI in healthcare was also a significant predictor (b = 0.2, β = .182, p = .035).

General trust in AI in healthcare was a significant predictor in all five models that reached statistical significance and was the strongest predictor of trust

in the AI application specifically. To examine this further, each of the five models was rerun with general trust in AI in healthcare removed from the set of predictors. In its absence, AI attitude and technology attitude became the strongest and most frequent predictors. For example, AI attitude ($\beta = .399$) and technology attitude ($\beta = .218$) emerged as the leading predictors for trust in the AI application. This closely resembles the findings of Kauttonen et al. (2025), who found technology attitude as one of the main drivers of trust and intention.

The regression models for the remaining outcomes were not statistically significant and were therefore dropped from further analysis.

To examine whether self-reported AI knowledge demonstrated the inverted U-shaped relationship reported by Kauttonen et al. (2025), a centred quadratic AI knowledge term was included in each regression model. None of the quadratic terms reached statistical significance, indicating that the hypothesised non-linear relationship was not observed in the present sample.

Regression diagnostics indicated that the assumptions of the models were generally satisfied. Inspection of residual plots and Cook's distance identified no influential observations or substantial violations of the regression assumptions.

Overall, the regression analyses showed that technology- and AI-related attitudes explained substantially more variation in customer acceptance than demographic or health-related characteristics. General trust in AI in healthcare emerged as the strongest predictor of trust in the AI application, whereas technology attitude was the strongest predictor of behavioural intention. No evidence was found for a quadratic relationship between AI knowledge and any of the outcome constructs.

5 Discussion

The aim of this study was to investigate the potential of AI-driven oculomics-based cardiovascular screening in optical retail settings. The study focused on customer acceptance of the AI-based screening service in optical retail settings. To achieve this purpose, three research questions were posed to guide the quantitative empirical research. First, the study explored how customers perceive the AI-based cardiovascular screening in optical retail settings. Second, the empirical data were analysed to identify factors that influence acceptance of such services. Third, the findings were assessed from the perspective of the operational implications of using oculomics screening in combination with optician retail services. In the following sections, the findings are reflected in answers to these questions and in relation to existing knowledge on the topic.

5.1 Theoretical implications

The results reported in Chapter 4 answer the questions how customers perceive the screening process in an optical retail setting, and what factors shape their perceptions. Correlation, subgroup and regression analysis were used to address these questions.

The correlation analysis revealed that the measured constructs clustered into conceptually coherent groups. Three clusters emerged: a technology and AI disposition cluster, a service evaluation cluster and a “explainability”-related cluster.

The first cluster consisted of variables measuring respondents’ technological affinity, which included AI knowledge, AI experience, technology attitude, AI attitude and IT skills. The strong correlations between these constructs were expected, as respondents with strong skills and knowledge of technology also tend to have more positive attitudes towards technology and AI. Similar clustering was also reported by Kauttonen et al. (2025), suggesting that these constructs reflect a broader underlying disposition to digital technologies. This cluster also helps explain the pattern observed in the subgroup comparisons below. As these constructs move together, a difference in one of these constructs due to demographics is usually observable in another as well.

The second cluster is of perceptions of the screening service itself. Appropriateness of the setting, perceived usefulness, understanding of the service and intention were all strongly associated with one another. The strongest correlation in the dataset is found between appropriateness of the setting and intention to use the service, both of which are the primary outcome constructs

in this study. From a service-dominant logic perspective, these findings suggest that respondents' willingness to use the service was closely connected to how well they understood it, found it useful and considered the setting appropriate for its implementation. These findings also fit into the Health Belief Model, which ties together perceived ease of use, perceived usefulness and behavioural intention to use. The corresponding constructs in this cluster are appropriateness of the setting, usefulness and intention, all of which are strongly correlated.

A third, smaller and weaker cluster was observed among variables relating to information about the AI system, including its developer, training data and processes (*explainability*). Moderate correlations between these constructs ($.41 \leq \rho \leq .43$) suggest that respondents who wished to receive information about one aspect of the AI application were also likely to expect information about the others. Similar relationships between these three constructs were reported by Kauttonen et al. (2025), although at a much higher level ($\rho > .7$). Their study also reported a strong correlation between training data and privacy, which was not observed in this sample (0.71 vs 0.20). It seems that customers here did not find training data to be nearly as important an issue as privacy.

Finally, trust in this AI application was associated with both technology disposition and service evaluation. Higher trust in the application was related to greater general trust in AI in healthcare, more positive AI attitudes, and more positive technology attitudes. Additionally, trust showed moderate positive association with understanding of the service, appropriateness of the setting and intention to use. Interestingly, while Kauttonen et al. reported a very strong correlation between trust and intention ($\rho = .808$), the same relationship in the present study was only moderate ($\rho = .34$). This could indicate that in this context, intention to use the service does not depend solely on trust but on a broader evaluation of the service aspects.

The role of demographic and health-related variables in technology acceptance

The subgroup analyses showed that participants' evaluations of the AI-based screening service were largely consistent across sociodemographic characteristics. Although age, gender and education level resulted in differences in general technology and AI disposition, these differences did not translate into differences in the primary outcome constructs measuring acceptance of the AI-supported screening service. Given the clustering identified above, in which technology disposition and service evaluation form related but distinct groups, this indicates that demographic characteristics shaped how comfortable respondents were with technology in general, without shaping how they evaluated this specific service.

Age-related differences were observed for technology related items only. Younger participants reported greater AI experience, AI knowledge, IT skills and more positive attitudes toward technology and AI than older participants. These findings are consistent with previous research showing that older individuals have less digital literacy and exposure to emerging technology (Estrela et al., 2023). Despite this difference in technological readiness, respondents across all age groups evaluated the AI-supported screening similarly. This suggest that age alone may not be a barrier to the acceptance of the service, when it is perceived as useful and appropriate. In fact, older participants were overrepresented in the study, which may itself indicate genuine interest in the service despite comparatively low technology experience.

A similar pattern was observed for gender. Men reported more positive attitudes towards technology and AI, as well as higher self-rated AI knowledge, AI experience and IT skills than women. No significant differences were observed in constructs measuring the acceptance of the service. This indicates that despite differences in self-perceived technological competence, men and women evaluated the screening service in similar ways.

Education level produced the strongest demographic differences in technology-related constructs. Participants with higher education levels reported greater technological affinity. These findings are unsurprising, as higher education is often associated with more exposure to digital technologies and digital literacy. However, similar to the age and gender comparisons, educational differences did not extend to evaluations of the service. Together, the age, gender and education comparisons suggest that acceptance of the service was not directly associated with the respondent's demographic background.

Wearable technology use was the only subgroup characteristic with statistical differences in both technology disposition and primary outcome constructs. Participants who used wearable devices reported more positive technology attitudes and greater technology skills, as well as higher perceived usefulness, appropriateness of setting, trust and intention to use the service. Although the observed effect sizes were small ($r < 0.189$), the fact that they were found across all primary outcome constructs suggest that prior experience with consumer health technologies may facilitate acceptance of AI-supported healthcare services. Individuals who use personal health devices might generally be more attentive of their health and well-being. This can be viewed through the Health Belief Model (Rosenstock et al., 1988), in which health motivation or self-efficacy is thought to influence the likelihood of taking preventive action. In this case, wearable technology use may serve as a proxy for health motivation, offering insight into how capable individuals feel of influencing their own health.

Overall, the subgroup analyses indicate that while demographic characteristics influenced respondents' general technological disposition, they had little impact on perceptions of the AI application and service. Instead, experience with digital health technologies, represented here by wearable technology use, was a more consistent differentiator. Familiarity with related technologies, rather than who a customer is, is what shapes acceptance, which has also been echoed in previous studies (Chung & Tan, 2025).

The impact of technological affinity and trust

The regression analysis reinforces the findings of the correlation and subgroup analysis above: technology- and AI-related constructs added more explanatory power than either demographic or health-related variables. This suggests that a customer's technological affinity and knowledge of AI generally predominantly shapes their trust, acceptance and intention to use the screening service. This is surprising as customers themselves are not the direct users of the AI system, the professional operating it is. They do, however see themselves and the AI system as an integral part of the value creation of the service rather than treating AI as a separable, background technical component.

General trust in AI in healthcare was the strongest and most consistent predictor in the five significant models and was the strongest predictor for trust in the AI application. This differs from Kauttonen et al. (2025), who found general technology and AI attitudes to be the primary drivers of trust. In their design, however, general healthcare AI trust was treated as an outcome instead of a predictor. When the models in this study were recalculated without this construct, they showed a similar pattern to Kauttonen et al. (*ibid.*) with AI and technology attitudes emerging as leading predictors. What this study suggests is that general trust in AI healthcare is closely related to, and possibly shaped by, the broad technology attitude of the customer.

Another difference to Kauttonen et al. (2025) findings concerns gender. In the present study, gender was a negative predictor in the model for intention, indicating that men were more cautious of using the service than women. This is the opposite of Kauttonen et al.'s finding that women are more cautious. This may be due to the small sample size of this study or the different analytical approach. Kauttonen et al. used gradient boosted tree models that also captured nonlinear interactions, whereas this study used simple linear regression.

5.2 Managerial implications

The findings of this study carry several practical implications for optical retailers considering the introduction of AI-supported health screening services.

First, the gap between the customers expectation for explainability and their actual understanding of the AI component has direct implications for service design and communication. While customers strongly agreed that AI-generated results should be presented clearly and expressed interest in knowing how the AI reaches its conclusions, fewer than half felt they understood how AI was actually used in the service. This suggests that having a reliable AI application is not enough; staff need to be equipped and trained to communicate, sometimes in simple terms, what the AI does and how it comes to its conclusions. Investment in this communicative layer of the service is likely to matter as much, if not more, for customer trust as the underlying technical performance of the AI itself. This need for clear communication also extends to how the service is marketed and launched, with the AI component explained in simple, non-technical terms. Customers with lower technological affinity appeared more apprehensive toward the service, and this could be mitigated by pairing marketing communication with educational information of the technology.

Second, the results support repositioning the value proposition of optical retail from a provider of vision correction and eyewear toward a broader health partner. Customers agreed that the screening would add value to a regular eye exam and that the combination felt natural. The screening service would therefore be most effectively marketed as an extension of existing service and retail relationship, not as a standalone diagnostic product. The existing retail relationship will need to extend beyond communicating the technologies described above, to also listening and encouraging customers who have lower technology competency, concerns or hesitation.

Third, because customers have a strong expectation for a professional to review AI-generated results, a human must remain in the loop when interpreting and communicating outcomes. This raises practical questions that providers will need to resolve: whether a professional reviews every result or only those flagged as high-risk, and what effect this has on their workload. Regardless of how this is resolved, the meaning of the results and recommended next steps need to be communicated in a way customers can understand and act on. The limitations of the validity of the screening results should also be communicated, underlining that the AI output is preliminary, and intended to guide customers toward primary healthcare providers rather

than serve as a conclusive diagnosis. The follow up after the imaging appointment is key to ensure the value is delivered.

Finally, how and to whom the service is marketed should take this study's results into account. Instead of targeting specific demographic segments, initial marketing should aim to reach customers with an existing affinity for technology, such as wearable technology users. This group is likely to represent the early-adopter segment in the Diffusion of Innovations framework (Rogers, 2003). Through this group the service could then diffuse to a wider customer base, provided that the service continues to demonstrate relative advantage, compatibility, and observable benefit over time.

5.3 Limitations

Several limitations should be considered when interpreting the findings of this study. First, the study sample was not fully representative of the target population for AI-supported CVD risk screening. The pilot was conducted in a single optic retail store, whose customer base consists primarily of older adults. Thus, men and individuals under 50 years of age were underrepresented, and women and participants over 60 years old were overrepresented. The appointment times for the screening service may have further contributed to this, as appointments were offered almost entirely during standard working hours on weekdays, which likely limited participation among working-age individuals. This is particularly relevant because the purpose of CVD risk screening is to identify individuals with increased risk early enough to provide preventative action. In addition, the sample was more highly educated than the general Finnish population aged 40-69 years (Tilastokeskus, 2026), which may have influenced participants' technological readiness and attitudes towards AI.

A second limitation is selection bias. Participants volunteered to participate in the pilot service and accompanying survey. Individuals who chose to attend the screening were likely already interested in preventative healthcare and more willing to engage with new health technologies than those who declined participation. This explains the generally positive attitudes towards technology, AI and the service itself observed in the sample. Findings in this study may overestimate the acceptance of AI-supported screening services compared with the broader target population. An attempt was made to mitigate this bias. Customers who received an invitation but did not book appointments were contacted by phone and asked why they had chosen not to receive the service. However, due to time constraints and a low response rate to the calls, the resulting sample was small (n = 15) and was not included in the final study. The answers that were obtained suggested that missing the

invitation and not meeting the eligibility criteria were the most common reasons for non-participation.

The measurement items also have possible limitations. While several constructs were adapted from previously validated questionnaires (Baldus et al., 2026; Fritsch et al., 2022; Kauttonen et al., 2025), a number of items and constructs were developed specifically for this study to measure the acceptance of the screening service. Although the internal consistency of these newly developed constructs were comparable to that of the previously validated constructs, they have not undergone independent validation. Therefore, it cannot be fully promised that the items measure the intended underlying constructs with the same validity as established constructs.

The study was exploratory in nature, and the relatively small sample size limited the statistical power of some analyses. Compared with previous studies in this field, such as Kauttonen et al. (2025), which included more than 1000 respondents, the 184 participants sampled in this study was considerably smaller. The explanatory power of the regression models was low to moderate, with the models explaining 9-36% of the variance in the outcome variables. While these values are comparable to those in previous studies (Kauttonen < 23%), it is nonetheless evidence that a substantial proportion of the variance remained unexplained.

Finally, the questionnaire did not collect information about the participants' educational field or professional background, for example, whether they worked in healthcare or a technology-related field. Professional experience may influence familiarity with AI, trust in healthcare technologies and perceptions of their appropriate use. As a result, this study did not assess whether occupational background contributed to participants' responses.

5.4 Future research

The limitations mentioned above point to several directions for future research. First, studies drawing on more diverse and representative samples are needed to establish whether the largely positive attitudes observed here hold true beyond the already self-selected group of participants. In particular, future research should aim to reach individuals who do not already engage with preventative health services or who decline participation when offered, since this group is arguably the one such services most need to reach. As noted above, attempts to contact non-participants in this study yielded only a small number of responses; more resource-intensive approaches, such as a dedicated follow-up study or interviews with decliners may be needed to understand that group's reasoning. Similarly, because respondents in this study completed the questionnaire prior to undergoing the imaging required

for the screening service, their responses reflected anticipated acceptance rather than evaluations based on actual experience with the service. Future research might examine the attitudes afterward to establish the attitude of actual experience.

Second, future research should examine the economic dimensions of AI-supported screening in retail settings. This study did not assess customers' willingness to pay for the service, which is an important consideration if the service moves toward from a free-of-charge pilot to a commercial offering. On a more general level, health economic evaluations are needed to assess the cost-effectiveness of oculomics-based screening relative to traditional CVD risk assessment. An evaluation of its downstream effects on healthcare resource use is also needed.

Third, research is needed on how the human oversight of AI-supported screening evolves as the underlying technologies evolve. In this study, customers expressed a strong preference for a professional's review of the AI-based results, which is echoed by many other studies that patients favor AI as a tool rather than a decision-maker. Whether this expectation will change as AI systems become more validated and adopted, and individuals' technology competencies increase remains to be seen. Future research could examine how customers want the results to be explained in practice.

Finally, the broader innovation landscape surrounding AI in healthcare is changing, with multinational companies increasingly funding research and development that was previously concentrated in public and academic institutions (Liu, 2026). Future research could examine how this change in funding entities shapes the priorities and standards of AI-based screening tools, such as the one piloted in this study.

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Appendices

A.1 Complete questionnaire in Finnish

Suhtautuminen tekoälyavusteiseen sydän- ja verisuonitautien seulontaan optikkoliikkeessä

Tässä kyselyssä kartoitetaan näkemyksiä sydän- ja verisuonitautien (CVD) riskiseulonnasta, joka toteutetaan optikkoliikkeessä silmänpohjakuvauksen ja tekoälyn avulla. Kysely on osa Aalto-yliopistolle tehtävää diplomityötä. Palvelussa sinusta otetaan silmänpohjakuvat, joista tekoäly arvioi sydän- ja verisuonitautien riskin. Silmänpohjakuvat analysoi tekoäly, joka on kehitetty arvioimaan sydän- ja verisuonitautien riskitekijöitä. Kyselyyn vastaaminen kestää noin 10–15 minuuttia.

Vastaukset käsitellään luottamuksellisesti ja anonyymisti. Tietosuojaseloste on annettu ennen kyselyyn vastaamista.

Mihin seuraavista ikäryhmistä kuulutte?

☐ 40-49 v.
☐ 50-59 v.
☐ Yli 60 vuotta täyttäneet

Sukupuoli

☐ Nainen
☐ Mies
☐ Muu
☐ En halua kertoa

Mikä on korkein suorittamanne koulutusaste?

☐ Peruskoulu
☐ Ammatillinen tutkinto
☐ Lukio / Ylioppilastutkinto
☐ Ammattikorkeakoulututkinto
☐ Ylempi amk-tutkinto
☐ Alempi korkeakoulututkinto
☐ Ylempi korkeakoulututkinto
☐ Muu, mikä? _____

Miten arvioisit yleistä terveydentilaasi viimeisten 12 kuukauden aikana?

☐ Erittäin huono
☐ Huono
☐ Ei hyvä eikä huono
☐ Hyvä
☐ Erittäin hyvä

Kuinka usein olet käyttänyt terveydenhuollonpalveluja viimeisen 12 kuukauden aikana?
Sisällytä kaikki käynnit terveydenhuollon ammattilaisten, kuten lääkäreiden, sairaanhoitajien, hammaslääkärien ja terapeuttien luona.

☐ Viikoittain tai useammin
☐ Muutaman kerran kuukaudessa
☐ Kuukausittain
☐ Muutaman kerran tai ei lainkaan

Onko sinulta aiemmin arvioitu sydän- ja verisuonitautien riskiä?

☐ Kyllä, ammattilaisen kanssa
☐ Kyllä, olen itse arvioinut
☐ Ei

Kuinka seuraava väittämä kuvaa ajatuksiasi terveydenhuoltopalvelujen nykytilasta?
Ota huomioon yleinen saatavuus, kustannukset ja laatu, sekä julkisella että yksityisellä sektorilla.

	Täysin eri mieltä	Eri mieltä	Ei samaa eikä eri mieltä	Samaa mieltä	Täysin samaa mieltä
Olen erittäin tyytyväinen nykyisiin terveydenhuoltopalveluihin.	○	○	○	○	○

Käytätkö teknologiaa, kuten älysormusta tai -kelloa terveytesi ja hyvinvointisi seurantaan?

☐ Kyllä
☐ Ei

Miten arvioisit IT-taitojasi?

☐ Erittäin huono
☐ Huono
☐ Keskimääräinen
☐ Hyvä
☐ Erittäin hyvä

Kuinka seuraavat väittämät kuvaavat asennettasi uutta teknologiaa kohtaan?

	Täysin eri mieltä	Eri mieltä	Ei samaa	Samaa mieltä	Täysin samaa mieltä

			eikä eri mieltä		
Seuraan uusien teknologisten tuotteiden kehitystä.	○	○	○	○	○
Kokeilen uusia teknologisia tuotteita muita aikaisemmin.	○	○	○	○	○
Olen valmis hyväksymään uusia teknologisia tuotteita	○	○	○	○	○
	○	○	○	○	○

Kuinka seuraavat väittämät kuvaavat tietämystäsi ja kokemustasi tekoälystä?

	Täysin eri mieltä	Eri mieltä	Ei samaa eikä eri mieltä	Samaa mieltä	Täysin samaa mieltä
Olen kuullut tai lukenut tekoälystä.	○	○	○	○	○
Minulla on vahva ymmärrys siitä, miten tekoäly toimii.	○	○	○	○	○
En voisi selittää mikä tekoäly on.	○	○	○	○	○
Minulla on kokemusta tekoälysovellusten käytöstä.	○	○	○	○	○

Kuinka seuraavat väittämät kuvaavat suhtautumistasi tekoälyyn?

	Täysin eri mieltä	Eri mieltä	Ei samaa eikä eri mieltä	Samaa mieltä	Täysin samaa mieltä
Tekoäly tarjoaa ratkaisuja moniin ongelmiimme.	○	○	○	○	○
Tekoälyn avulla kaikki on mahdollista.	○	○	○	○	○
Tunnen saavuttavani enemmän tekoälyn ansiosta.	○	○	○	○	○

Uskon, että tekoälyn käyttö tuo hyötyjä potilaalle.	○	○	○	○	○

Mikä sai sinut osallistumaan tähän tutkimukseen? Voit valita useita vaihtoehtoja.

☐ Haluan saada lisätietoa omasta sydän- ja verisuonitautiriskistäni
☐ Olen kiinnostunut ennaltaehkäisevästä terveydenhuollosta
☐ Olen kiinnostunut tekoälyn käytöstä terveydenhuollossa
☐ Haluan kokeilla uutta palvelua tai teknologiaa
☐ Seulonta on helppo tehdä näöntarkastuksen yhteydessä
☐ Haluan edistää tutkimusta
☐ Seulonta tarjotaan maksutta
☐ Haluan, että minusta otetaan silmänpohja- ja OCT-kuvat
☐ Muu syy, mikä? _____

Kuinka seuraavat väittämät kuvaavat luottamustasi tekoälyyn terveydenhuollon ja hyvinvoinnin sovelluksissa?

	Täysin eri mieltä	Eri mieltä	Ei samaa eikä eri mieltä	Samaa mieltä	Täysin samaa mieltä
Minun on helppo luottaa tekoälyyn.	○	○	○	○	○
Minä en luota tekoälyyn.	○	○	○	○	○
Luotan tekoälysovelluksiin, vaikka minulla on vain vähän tietoa siitä.	○	○	○	○	○

Arvioi, kuinka seuraavat väittämät kuvaavat mielipidettäsi tämän tekoälysovelluksen luotettavuudesta.

Tämä tekoälysovellus arvioi sydän- ja verisuonitautiriskin silmänpohjakuvasta.

	Täysin eri mieltä	Eri mieltä	Ei samaa eikä eri mieltä	Samaa mieltä	Täysin samaa mieltä
Luotan siihen, että tämä tekoälysovellus pystyy tekemään johtopäätöksiä terveyteni ja hyvinvointini suhteen.	○	○	○	○	○
Luotan tekoälypohjaisen analyysin tarkkuuteen.	○	○	○	○	○

Luotan siihen, että tämän tekoälyn avulla tehdyt johtopäätökset ovat vähintään yhtä hyviä kuin ihmisen tekemät päätökset.	○	○	○	○	○
Luotan siihen, että tämän tekoälysovelluksen tekemät johtopäätökset ovat parempia kuin ihmisen tekemät päätökset.	○	○	○	○	○
Haluaisin, että ammattilainen tarkistaisi tekoälyn tulokset.	○	○	○	○	○
Luotan siihen, että ammattilainen tulkitsee tekoälyn tulokset asianmukaisesti.	○	○	○	○	○

Kuinka seuraavat väittämät vastaavat mielipidettäsi tekoälyn tuloksista?

	Täysin eri mieltä	Eri mieltä	Ei samaa eikä eri mieltä	Samaa mieltä	Täysin samaa mieltä
Haluan tietää, kuinka tämä tekoäly tuottaa tuloksensa.	○	○	○	○	○
Minulle on tärkeää ymmärtää tämän tekoälyn tulosten ja päätösten taustalla olevat prosessit.	○	○	○	○	○
Tämän tekoälysovelluksen tuottamat tulokset tulisi selittää ja esittää ymmärrettävällä ja läpinäkyvällä tavalla.	○	○	○	○	○

Kuinka seuraavat väittämät kuvaavat mielipidettäsi tekoälyn koulutusdatasta?

	Täysin eri mieltä	Eri mieltä	Ei samaa eikä eri mieltä	Samaa mieltä	Täysin samaa mieltä
On erittäin tärkeää, että asiakkaat tietävät, kuinka paljon ja minkälaista dataa tämän tekoälyn koulutuksessa käytetään.	○	○	○	○	○
Tämän tekoälyn koulutuksessa käytetyn datan tyyppiä ja määrää ei tarvitse ilmoittaa asiakkaille.	○	○	○	○	○

Kuinka seuraavat väittämät kuvaavat mielipidettäsi tekoälyn kehittäjästä?

	Täysin eri mieltä	Eri mieltä	Ei samaa eikä eri mieltä	Samaa mieltä	Täysin samaa mieltä
Tämän tekoälysovelluksen kehittänyt teknologiayritys (esim. sen koko, sijaintimaa ja tunnettavuus) on ratkaisevan tärkeä luottamuksen rakentamisessa asiakkaiden keskuudessa.	○	○	○	○	○
Yritys, sen kotimaa ja brändin maine eivät ole ratkaisevan tärkeitä tietoja tämän tekoälysovelluksen asiakkaille.	○	○	○	○	○
Kaikkien käyttäjien tulisi tietää, mikä teknologiayritys on kehittänyt tämän tekoälysovelluksen.	○	○	○	○	○

Kuinka seuraavat väittämät vastaavat mielipidettäsi tekoälyn käyttämistä tiedoistasi?

	Täysin eri mieltä	Eri mieltä	Ei samaa	Samaa mieltä	Täysin samaa mieltä

			eikä eri mieltä		
En välitä siitä, missä tietoni säilytetään, kuka niitä voi tarkastella ja miten niitä käytetään.	○	○	○	○	○
Minulle on erittäin tärkeää tietää, miten ja missä tietoni säilytetään, kuka niihin pääsee käsiksi ja miten niitä käytetään.	○	○	○	○	○

Arvioi kuinka seuraavat väittämät vastaavat mielipidettäsi sydän- ja verisuonitautiriskin arvioinnista silmänpohjakuvista.

Nykyisin sydän- ja verisuonitautiriskin arviointi toteutetaan erilaisilla riskinarviointityökaluilla (esim. FINRISKI, SCORE ja Framingham), jotka laskevat riskit eri riskitekijöihin (mm. tupakointi, kohonnut verenpaine, korkea kolesteroli) perustuen. Sydän- ja verisuonitautiriskin arviointi silmänpohjakuvien ja tekoälyn avulla voisi olla uusi tapa seuloa sydän- ja verisuonitauteja väestöstä.

	Täysin eri mieltä	Eri mieltä	Ei samaa eikä eri mieltä	Samaa mieltä	Täysin samaa mieltä
Tämä tekoälypohjainen seulontapalvelu olisi hyödyllinen sydän- ja verisuonitautien riskin arvioinnissa.	○	○	○	○	○
Tämä seulontapalvelu auttaisi minua ryhtymään tarvittaessa ennaltaehkäiseviin toimiin.	○	○	○	○	○
Tämä sydän- ja verisuonitautiriskin arviointipalvelu lisäisi säännöllisen silmätarkastuksen arvoa.	○	○	○	○	○
Seulontaprosessi vaikuttaa selkeältä ja ymmärrettävältä.	○	○	○	○	○
Ymmärrän, miten tekoälyä käytetään tässä palvelussa.	○	○	○	○	○

Minusta olisi luontevaa osallistua sydän- ja verisuonitautiriskin seulontaan näöntarkastuksen yhteydessä.	○	○	○	○	○
Pelkään saavani virheellisiä tuloksia.	○	○	○	○	○
En olen huolissani tietojeni turvallisuudesta.	○	○	○	○	○
Mielestäni nämä tekoälysovellukset ovat alttiita tietoturvauhkille.	○	○	○	○	○
Optikkoliike on sopiva paikka sydän- ja verisuonitautien seulontaan.	○	○	○	○	○
Luotan optikkoliikkeessä tarjottaviin terveyspalveluihin.	○	○	○	○	○
Mieluummin käyn sydän- ja verisuonitautiriskin seulonnassa optikkoliikkeessä kuin sairaalassa tai muussa terveydenhuollon toimipisteessä.	○	○	○	○	○
Tämä ympäristö madaltaa kynnystä ennaltaehkäiseviin terveystarkastuksiin.	○	○	○	○	○
Olen todennäköisemmin valmis osallistumaan seulontaan, jos se tarjotaan täällä.	○	○	○	○	○
Valitsisin tämän seulontapalvelun tulevaisuudessa, jos sitä tarjotaan.	○	○	○	○	○
Suosittelisin tätä palvelua muillekin.	○	○	○	○	○

Onko vielä jotakin, mitä haluaisit kertoa suhtautumisestasi kyseiseen palveluun?

Kiitos kun osallistuit kyselyyn!
Jos sinulla herää kysymyksiä, tai haluat antaa palautetta, voit olla yhteydessä:
Aino Soinio, aino.soinio@aalto.fi

A.2 Complete questionnaire in English

Attitudes toward AI-assisted screening of cardiovascular diseases in an optical retail setting

This survey aims to gather opinions on cardiovascular disease (CVD) risk screening using fundus photography and artificial intelligence at an optic retail store. The survey is part of a master's thesis being conducted at Aalto University. During the service, fundus images of your eyes will be taken, which artificial intelligence will use to assess your risk of cardiovascular disease. The fundus images are analysed by an artificial intelligence developed to assess risk factors for cardiovascular disease. Completing the survey takes about 10–15 minutes.

Responses will be processed confidentially and anonymously. A privacy policy has been provided before you answer the survey.

Which of the following age groups do you belong to?

☐ 40-49 years
☐ 50-59 years
☐ Over 60 years

Gender

☐ Female
☐ Male
☐ Other
☐ Prefer not to say

What is your highest level of education?

☐ Basic education
☐ Vocational college
☐ High school / Matriculation examination
☐ Bachelor's degree (University of Applied Sciences)
☐ Master's degree (University of Applied Sciences)
☐ Bachelor's degree (University)
☐ Master's degree (University)
☐ Other: ____

How would you rate your general health over the past 12 months?

☐ Very poor
☐ Poor
☐ Neither good nor poor
☐ Good
☐ Very good

How often have you used healthcare services during the past 12 months?
Include all visits to healthcare professionals, such as medical doctors, nurses, dentists and therapists.

☐ Weekly or more
☐ A few times per month
☐ Monthly
☐ A few times or not at all

Have you previously had your cardiovascular disease risk assessed?

☐ Yes, with a professional
☐ Yes, I have assessed it myself
☐ No

How does the following statement describe your opinion on the current state of healthcare services?
Consider overall availability, cost and quality, including both public and private sector.

	Strongly disagree	Disagree	Neither disagree nor agree	Agree	Strongly agree
I am very satisfied with current healthcare services.	○	○	○	○	○

Do you use technology such as a smart ring or smartwatch to monitor your health and well-being?

☐ Yes
☐ No

How would you rate your IT skills?

☐ Very poor
☐ Poor
☐ Average
☐ Good
☐ Very good

How do the following statements describe your attitude toward new technologies?

	Strongly disagree	Disagree	Neither disagree nor agree	Agree	Strongly agree
I follow the development of new technological products.	○	○	○	○	○
I try new technological products before others.	○	○	○	○	○
I am willing to adopt new technological products.	○	○	○	○	○
	○	○	○	○	○

How do the following statements describe your knowledge and experience of AI?

	Strongly disagree	Disagree	Neither disagree nor agree	Agree	Strongly agree
I have heard or read of AI.	○	○	○	○	○
I have a strong understanding of how artificial intelligence works.	○	○	○	○	○
I couldn't explain what AI is.	○	○	○	○	○
I have experience in using AI applications.	○	○	○	○	○

How do the following statements describe your attitude toward artificial intelligence?

	Strongly disagree	Disagree	Neither disagree nor agree	Agree	Strongly agree
AI offers solutions to many of our problems.	○	○	○	○	○

With AI anything is possible.	○	○	○	○	○
I feel that I achieve more because of AI.	○	○	○	○	○
I believe that the use of artificial intelligence brings benefits for the patient.	○	○	○	○	○

What motivated you to participate in this study? You may select multiple options.

☐ I want more information about my cardiovascular risk.
☐ I am interested in preventive healthcare.
☐ I am interested in the use of AI in healthcare.
☐ I want to try a new service or technology.
☐ The screening is easy to do alongside an eye exam.
☐ I want to advance research.
☐ The screening is offered free of charge.
☐ I want to receive fundus and OCT images.
☐ Other:_____

How do the following statements describe your trust in AI applications in healthcare and well-being?

	Strongly disagree	Disagree	Neither disagree nor agree	Agree	Strongly agree
It is easy for me to trust AI applications. (Kauttonen)	○	○	○	○	○
I don't trust AI.	○	○	○	○	○
I trust AI applications even if I have little information about it. (Kauttonen)	○	○	○	○	○

How do the following describe your opinion of trust in this AI application?

	Strongly disagree	Disagree	Neither disagree nor agree	Agree	Strongly agree
I trust that this AI application can make	○	○	○	○	○

conclusions regarding my health and well-being.					
I trust the accuracy of AI-based analysis.	○	○	○	○	○
I trust that conclusions made by this AI are at least as good as those made by humans.	○	○	○	○	○
I trust that conclusions made by this AI application are better than those made by humans.	○	○	○	○	○
I would like a professional to review the AI's results.	○	○	○	○	○
I trust that a professional interprets the AI's results appropriately.	○	○	○	○	○

How do the following describe your opinion of the results made by this AI application?

	Strongly disagree	Disagree	Neither disagree nor agree	Agree	Strongly agree
I want to know how this AI produces its results.	○	○	○	○	○
It is important for me to understand the processes behind the results and decisions of this AI.	○	○	○	○	○
The results produced by this AI application should be explained and presented in a clear and transparent manner.	○	○	○	○	○

How do the following describe your opinion on the training data of this AI?

	Strongly disagree	Disagree	Neither disagree nor agree	Agree	Strongly agree
It is very important that customers know how much and what kind of data was used to train this AI system	○	○	○	○	○
The type and quantity of data used to train this AI system do not need to be disclosed to the customer.	○	○	○	○	○

How do the following describe your opinion related to the developer of this AI?

	Strongly disagree	Disagree	Neither disagree nor agree	Agree	Strongly agree
The technology company developing this AI system (e.g., its size, country and familiarity) are crucial in building trust with users	○	○	○	○	○
The company, its home country, and brand reputation are not crucial information for users of this AI application.	○	○	○	○	○
All users should know which technology company developed this AI application.	○	○	○	○	○

How do the following describe your opinion on your data used by this AI?

	Strongly disagree	Disagree	Neither disagree	Agree	Strongly agree

			nor agree		
I do not care where my data is stored, who can access it, or how it is used.	○	○	○	○	○
It is very important for me to know how and where my data is stored, who can access it, and how it is used.	○	○	○	○	○

How do the following statements describe your opinions on the evaluation of cardiovascular disease risk from retinal images?
Currently, CVD risk is assessed using various risk assessment tools (e.g., FINRISKI, SCORE, and Framingham), which calculate risk based on different risk factors (such as smoking, high blood pressure, and high cholesterol). Assessing the risk of cardiovascular disease using fundus images and artificial intelligence could be a new way to screen the population for cardiovascular disease.

	Strongly disagree	Disagree	Neither disagree nor agree	Agree	Strongly agree
This AI-based screening service would be useful in assessing cardiovascular disease risk.	○	○	○	○	○
This screening service would help me take preventive actions if necessary.	○	○	○	○	○
This CVD risk assessment service would increase the value of regular eye examinations.	○	○	○	○	○
The screening process seems clear and understandable.	○	○	○	○	○

I understand how AI is used in this service.	○	○	○	○	○
It would feel natural for me to participate in CVD risk screening alongside an eye exam.	○	○	○	○	○
I am afraid of receiving incorrect results.	○	○	○	○	○
I am not concerned about the safety of my data.	○	○	○	○	○
In my opinion, these AI applications are vulnerable to cybersecurity threats.	○	○	○	○	○
An optic retail store is an appropriate place for cardiovascular disease screening.	○	○	○	○	○
I trust the healthcare services provided in an optic retail store.	○	○	○	○	○
I would rather attend screening in an optic retail store than in a hospital or other healthcare facility.	○	○	○	○	○
This environment lowers the threshold for preventive health check-ups.	○	○	○	○	○
I am likely to be more willing to participate in screening if it is offered here.	○	○	○	○	○
I would choose this screening service in the future if it is available.	○	○	○	○	○
I would recommend this service to others.	○	○	○	○	○

Is there anything else you would like to share about your attitude toward this service?

Thank you for participating in the survey!
If you have any questions or would like to provide feedback, please contact:
Aino Soinio, aino.soinio@aalto.fi

A.3 Survey questions and response options

Questions with asterisk (*) are reverse scored. Bolded item names are composite constructs.

Questionnaire section 1

Item	Question	Options
Age group	Which of the following age groups do you belong to?	40-49 years ; 50-59 years; Over 60 years
Gender	Gender	Female; Male; Other; Prefer not to say
Education level	What is your highest level of education?	Basic education; Vocational college; High school / Matriculation examination; Bachelor's degree (University of Applied Sciences); Master's degree (University of Applied Sciences); Bachelor's degree (University); Master's degree (University); Other: ____
Health status	How would you rate your general health over the past 12 months?	Very poor; Poor; Neither good nor poor; Good; Very good
Health service usage	How often have you used healthcare services during the past 12 months?	Weekly or more; A few times per month; Monthly; A few times or not at all
Prior CVD screening	Have you previously had your cardiovascular disease risk assessed?	Yes, with a professional; Yes, I have assessed it myself; No
Healthcare satisfaction	I am very satisfied with current healthcare services.	5-point Likert scale (disagree to agree)
Wearable technology use	Do you use technology such as a smart ring or smartwatch to monitor your health and well-being?	Yes; No

IT skills	How would you rate your IT skills?	Very poor; Poor; Average; Good; Very good
Technology attitude	I follow the development of new technological products.	5-point Likert scale
	I try new technological products before others.	5-point Likert scale
	I am willing to adopt new technological products.	5-point Likert scale
AI knowledge	I have heard or read of AI.	5-point Likert scale
	I have a strong understanding of how artificial intelligence works.	5-point Likert scale
	I couldn't explain what AI is.*	5-point Likert scale
AI attitude	AI offers solutions to many of our problems.	5-point Likert scale
	I feel that I achieve more because of AI.	5-point Likert scale
	I believe that the use of artificial intelligence brings benefits for the patient.	5-point Likert scale
AI_attitude_2	With AI anything is possible.	5-point Likert scale
Reason for participation	What motivated you to participate in this study?	I want more information about my cardiovascular risk.; I am interested in preventive healthcare.; I am interested in the use of AI in healthcare.; I want to try a new service or technology.; The screening is easy to do alongside an eye exam.; I want to advance research.; The screening is offered free of charge.; I want to receive fundus and OCT images.; Other:_____
Trust in healthcare AI	It is easy for me to trust AI applications.	5-point Likert scale
	I don't trust AI. *	5-point Likert scale
	I trust AI applications even if I have little information about it.	5-point Likert scale

Questionnaire section 2

All response options are 5-point Likert scale

Item	Questions

Trust	I trust that this AI application can make conclusions regarding my health and well-being.
	I trust the accuracy of AI-based analysis.
	I trust that conclusions made by this AI are at least as good as those made by humans.
	I trust that conclusions made by this AI application are better than those made by humans.
Human trust	I would like a professional to review the AI's results.
	I trust that a professional interprets the AI's results appropriately.
Explainability	I want to know how this AI produces its results.
	It is important for me to understand the processes behind the results and decisions of this AI.
	The results produced by this AI application should be explained and presented in a clear and transparent manner.
Training data	It is very important that customers know how much and what kind of data was used to train this AI system
	The type and quantity of data used to train this AI system do not need to be disclosed to the customer. *
Developer	The technology company developing this AI system (e.g., its size, country and familiarity) are crucial in building trust with users
	The company, its home country, and brand reputation are not crucial information for users of this AI application. *
	All users should know which technology company developed this AI application.
Privacy	I do not care where my data is stored, who can access it, or how it is used.
	It is very important for me to know how and where my data is stored, who can access it, and how it is used.

Questionnaire section 3.

All response options are 5-point Likert scale.

Item	Question
Usefulness	This AI-based screening service would be useful in assessing cardiovascular disease risk.
	This screening service would help me take preventive actions if necessary.
	This CVD risk assessment service would increase the value of regular eye examinations.
Understand	The screening process seems clear and understandable.
	I understand how AI is used in this service.
Appropriateness of setting	It would feel natural for me to participate in CVD risk screening alongside an eye exam.

	An optic retail store is an appropriate place for cardiovascular disease screening.
	I trust the healthcare services provided in an optic retail store.
	I would rather attend screening in an optic retail store than in a hospital or other healthcare facility.
	This environment lowers the threshold for preventive health check-ups.
	I am likely to be more willing to participate in screening if it is offered here.
Intention	I would choose this screening service in the future if it is available.
	I would recommend this service to others.
Accuracy	I am afraid of receiving incorrect results.
Data safety 1	I am not concerned about the safety of my data.
Data safety 2	In my opinion, these AI applications are vulnerable to cybersecurity threats.

A.4 Descriptive statistics for variables

Variable	mean	median	sd	min	max	range	skew	kurtosis	se
age_group	2.2228	2	0.7677	1	3	2	-0.3980	-1.2174	0.0566
gender	1.2717	1	0.4461	1	2	1	1.0179	-0.9691	0.0329
education_level	2.8370	3	0.9087	1	4	3	-0.1542	-1.0082	0.0670
education_open	3.1667	3.5	1.4720	1	5	4	-0.2323	-1.7165	0.6009
health_status	3.9293	4	0.6615	2	5	3	-0.8253	1.6026	0.0488
health_service_usage	3.7826	4	0.5295	1	4	3	-2.5867	6.6534	0.0390
prior_cvd_screening	2.5761	3	0.7715	1	3	2	-1.3898	0.1205	0.0569
healthcare_satisfaction	3.2500	3	1.0149	1	5	4	-0.1677	-0.8853	0.0748
tech_wearable	1.5326	2	0.5003	1	2	1	-0.1296	-1.9939	0.0369
IT_skills	3.7935	4	0.7898	2	5	3	0.0479	-0.8205	0.0582
technology_attitude_1	3.6739	4	0.9537	1	5	4	-0.5940	0.0098	0.0703
technology_attitude_2	2.8261	3	1.0672	1	5	4	0.1597	-0.7007	0.0787
technology_attitude_3	4.1359	4	0.6839	2	5	3	-0.4817	0.2503	0.0504
AI_knowledge_1	4.5924	5	0.5249	3	5	2	-0.7090	-0.7901	0.0387
AI_knowledge_2	3.5380	4	0.8612	1	5	4	-0.2446	-0.3950	0.0635
AI_knowledge_3	2.2337	2	1.0053	1	5	4	0.5830	-0.0844	0.0741
AI_knowledge_3_r	3.7663	4	1.0053	1	5	4	-0.5830	-0.0844	0.0741
AI_experience	3.7772	4	1.1544	1	5	4	-0.8972	-0.0205	0.0851
AI_attitude_1	4.0000	4	0.7090	2	5	3	-0.3659	0.0105	0.0523
AI_attitude_2	2.5000	2	0.9524	1	5	4	0.1887	-0.4670	0.0702
AI_attitude_3	3.2609	3	0.8916	1	5	4	-0.4840	0.1614	0.0657
AI_attitude_4	4.0652	4	0.6982	1	5	4	-1.0459	3.2380	0.0515
motiv_cvd_info	0.8533	1	0.3548	0	1	1	-1.9804	1.9327	0.0262
motiv_preventive	0.7989	1	0.4019	0	1	1	-1.4794	0.1897	0.0296
motiv_AI_interest	0.5815	1	0.4947	0	1	1	-0.3278	-1.9028	0.0365
motiv_new_service	0.5000	0.5	0.5014	0	1	1	0.0000	-2.0108	0.0370
motiv_convenience	0.3207	0	0.4680	0	1	1	0.7623	-1.4266	0.0345
motiv_research	0.7989	1	0.4019	0	1	1	-1.4794	0.1897	0.0296
motiv_free	0.6685	1	0.4720	0	1	1	-0.7099	-1.5041	0.0348
motiv_retinal_images	0.7500	1	0.4342	0	1	1	-1.1453	-0.6920	0.0320
motiv_other	0.0163	0	0.1270	0	1	1	7.5765	55.7066	0.0094
motiv_other_open	2.0000	2	1.0000	1	3	2	0.0000	-2.3333	0.5774

HC_AI_trust_1	3.1957	3	0.7501	1	5	4	-0.2551	0.1866	0.0553
HC_AI_trust_2	2.5217	2.5	0.7535	1	5	4	0.1933	0.0152	0.0556
HC_AI_trust_2_r	3.4783	3.5	0.7535	1	5	4	-0.1933	0.0152	0.0556
HC_AI_trust_3	3.0326	3	0.7955	1	5	4	-0.3167	0.2448	0.0586
trust_1	3.7337	4	0.5724	2	5	3	-0.1052	-0.2301	0.0422
trust_2	3.6033	4	0.6007	1	5	4	-0.3237	0.8223	0.0443
trust_3	3.3859	3	0.7152	1	5	4	-0.0881	0.1253	0.0527
trust_4	2.9022	3	0.6106	1	5	4	0.3389	1.6755	0.0450
human_trust_1	4.3641	4	0.6470	3	5	2	-0.5130	-0.7030	0.0477
human_trust_2	4.4511	4	0.5204	3	5	2	-0.0369	-1.4735	0.0384
explainability_1	4.0217	4	0.7389	2	5	3	-0.5189	0.1918	0.0545
explainability_2	3.7609	4	0.8476	1	5	4	-0.4923	-0.0149	0.0625
explainability_3	4.2500	4	0.6795	2	5	3	-0.5586	0.0548	0.0501
training_data_1	3.7609	4	0.7875	2	5	3	-0.2902	-0.2931	0.0581
training_data_2	2.5707	3	0.9440	1	5	4	0.1267	-0.6454	0.0696
training_data_2_r	3.4293	3	0.9440	1	5	4	-0.1267	-0.6454	0.0696
developer_1	3.7283	4	0.7907	2	5	3	-0.2093	-0.3915	0.0583
developer_2	2.5054	2	0.9114	1	5	4	0.3933	-0.4531	0.0672
developer_2_r	3.4946	4	0.9114	1	5	4	-0.3933	-0.4531	0.0672
developer_3	3.8424	4	0.8112	1	5	4	-0.4412	0.1074	0.0598
privacy_1	1.5054	1	0.7753	1	5	4	1.8014	3.5005	0.0572
privacy_1_r	4.4946	5	0.7753	1	5	4	-1.8014	3.5005	0.0572
privacy_2	4.3913	5	0.9287	1	5	4	-1.9020	3.6303	0.0685
usefulness_1	4.1576	4	0.5454	3	5	2	0.0852	0.0208	0.0402
usefulness_2	4.3043	4	0.5277	3	5	2	0.1586	-0.6951	0.0389
usefulness_3	4.2446	4	0.6005	3	5	2	-0.1534	-0.5496	0.0443
understand_1	3.8750	4	0.7018	2	5	3	-0.2963	0.0269	0.0517
understand_2	3.4239	3	0.8196	1	5	4	-0.2009	-0.0612	0.0604
appr_setting_1	4.3587	4	0.5347	3	5	2	0.0427	-0.9502	0.0394
accuracy	3.6250	4	0.7507	1	5	4	-0.1192	0.0879	0.0553
data_safety_1	3.0707	3	1.0663	1	5	4	-0.1128	-0.8567	0.0786
data_safety_1_r	2.9293	3	1.0663	1	5	4	0.1128	-0.8567	0.0786
data_safety_2	3.0326	3	0.7532	1	5	4	0.1760	0.5392	0.0555
appr_setting_2	3.7011	4	0.7188	1	5	4	-0.1067	0.2186	0.0530
appr_setting_3	4.0707	4	0.6778	1	5	4	-0.7135	1.8923	0.0500
appr_setting_4	3.4130	3	0.8703	1	5	4	-0.0059	0.4099	0.0642
appr_setting_5	4.0761	4	0.6813	2	5	3	-0.4034	0.1836	0.0502
appr_setting_6	4.0217	4	0.7240	2	5	3	-0.1183	-0.8544	0.0534
intention_1	4.2120	4	0.6475	3	5	2	-0.2311	-0.7209	0.0477
intention_2	4.1685	4	0.6926	3	5	2	-0.2331	-0.9330	0.0511

A.5 Subgroup comparison results

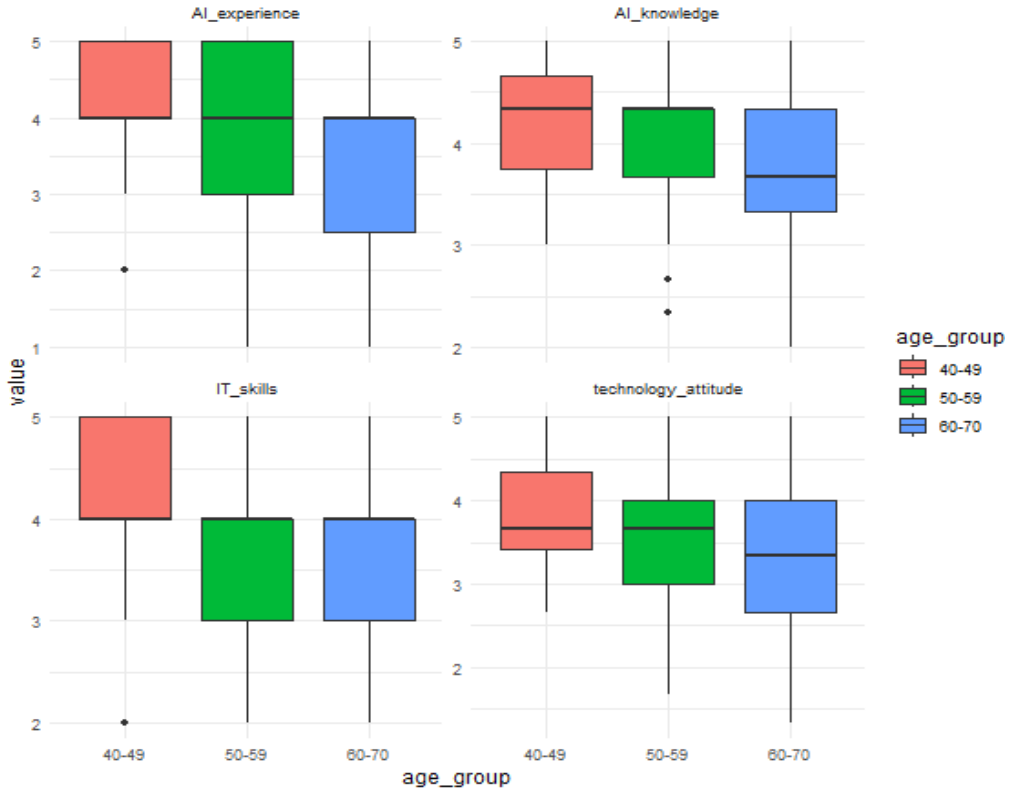
Full subgroup comparison results included below. Subgroups are age, gender, education level, prior CVD screening experience and wearable technology use.

Age subgroup comparison results

Outcome	Statistic H	*p*-value	Effect size ε^2
AI experience	16.049	0.000	0.078
AI knowledge	13.219	0.001	0.062
IT skills	12.467	0.002	0.058
Technology attitude	9.505	0.009	0.041
AI attitude	3.015	0.221	0.006
Data safety 2	2.742	0.254	0.004

Privacy	2.713	0.258	0.004
Developer	2.588	0.274	0.003
Human trust	2.367	0.306	0.002
Data safety 1	2.063	0.356	0.000
Usefulness	1.329	0.515	-0.004
Explainability	1.309	0.520	-0.004
Appr setting	1.303	0.521	-0.004
Intention	1.265	0.531	-0.004
Understand	1.239	0.538	-0.004
HC AI trust	0.921	0.631	-0.006
Training data	0.660	0.719	-0.007
Trust	0.379	0.827	-0.009
Accuracy	0.352	0.838	-0.009

Age group comparison box plots



Gender subgroup comparison results

Outcome	Statistic *U*	*p*-value	Effect size *r*
Technology attitude	1860.0	0.000	0.345
AI attitude	2452.5	0.004	0.210
AI experience	2586.0	0.012	0.185
AI knowledge	2586.5	0.016	0.177
IT skills	2756.0	0.048	0.146
Human trust	2866.0	0.112	0.117

Accuracy	3780.0	0.146	0.107
Intention	3671.0	0.290	0.078
Trust	3050.5	0.344	0.070
Appr setting	3514.5	0.607	0.038
Developer	3195.5	0.627	0.036
Understand	3220.5	0.679	0.031
HC AI trust	3263.0	0.784	0.020
Training data	3282.0	0.829	0.016
Explainability	3283.0	0.832	0.016
Usefulness	3289.5	0.843	0.015
Data safety 1	3319.5	0.923	0.007
Privacy	3365.5	0.959	0.004
Data safety 2	3353.0	0.993	0.001

Education subgroup comparison results

Outcome	Statistic H	*p*-value	Effect size ε^2
IT skills	21.932	0.000	0.105
AI experience	20.431	0.000	0.097
AI knowledge	17.455	0.001	0.080
AI attitude	16.962	0.001	0.078
Technology attitude	9.264	0.026	0.035
Human trust	7.042	0.071	0.022
Usefulness	6.189	0.103	0.018
Developer	4.482	0.214	0.008
HC AI trust	3.870	0.276	0.005
Intention	3.299	0.348	0.002
Appr setting	2.774	0.428	-0.001
Accuracy	2.524	0.471	-0.003
Training data	2.204	0.531	-0.004
Trust	2.116	0.549	-0.005
Explainability	1.628	0.653	-0.008
Privacy	1.531	0.675	-0.008
Understand	1.238	0.744	-0.010
Data safety 2	0.889	0.828	-0.012
Data safety 1	0.084	0.994	-0.016

Prior CVD screening subgroup comparison results

Outcome	Statistic *U*	*p*-value	Effect size *r*
Technology attitude	3781.5	0.050	0.145
HC AI trust	3762.0	0.055	0.141
AI experience	3684.5	0.086	0.127
AI attitude	3664.5	0.111	0.118
Developer	3549.5	0.224	0.090
Privacy	3523.0	0.224	0.090
AI knowledge	3511.5	0.276	0.080
Trust	3500.5	0.289	0.078
Intention	3414.0	0.417	0.060
Human trust	2954.5	0.459	0.055
Usefulness	3386.5	0.473	0.053
Training data	3356.0	0.552	0.044
IT skills	3346.0	0.558	0.043
Explainability	3015.5	0.606	0.038
Data safety 1	3323.0	0.622	0.036
Data safety 2	3286.0	0.689	0.030
Understand	3294.0	0.694	0.029
Accuracy	3252.0	0.787	0.020
Appr setting	3114.5	0.849	0.014

Wearable technology use subgroup comparison results

Outcome	Statistic *U*	*p*-value	Effect size *r*
Technology attitude	5674.0	0.000	0.301
AI knowledge	5301.5	0.002	0.225
AI experience	5140.5	0.007	0.200
Usefulness	5088.0	0.010	0.189
Appr setting	5002.0	0.028	0.162
IT skills	4921.0	0.036	0.155
Intention	4921.5	0.037	0.154
AI attitude	4946.0	0.039	0.152
Trust	4934.5	0.042	0.150
HC AI trust	4825.5	0.084	0.128
Training data	3770.0	0.207	0.093
Understand	4653.5	0.210	0.093
Data safety 2	3948.5	0.408	0.061
Data safety 1	4019.0	0.575	0.041
Privacy	4039.5	0.599	0.039
Developer	4346.0	0.711	0.027
Human trust	4092.0	0.722	0.026
Accuracy	4148.5	0.844	0.015
Explainability	4235.0	0.954	0.004

A.6 Correlations

Cluster 1

	cor (ρ)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1)	health_status	1								
(2)	health_service_usage	0.27	1							
(3)	healthcare_satisfaction	0.21	-0.12	1						
(4)	IT_skills	0.18	0.07	0.13	1					
(5)	technology_attitude	0.17	-0.06	0.23	0.51	1				
(6)	AI_knowledge	0.28	-0.03	0.15	0.54	0.49	1			
(7)	AI_experience	0.25	0.02	0.1	0.45	0.44	0.63	1		
(8)	AI_attitude	0.11	-0.05	0.19	0.31	0.55	0.41	0.49	1	
(9)	HC_AI_trust	0.1	0.01	0.22	0.14	0.34	0.15	0.13	0.48	1

Clusters 2 and 3

	cor (ρ)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
(10)	trust	1											
(11)	human_trust	0.05	1										
(12)	explainability	0.07	0.29	1									
(13)	training_data	-0.12	0.3	0.41	1								
(14)	developer	-0.04	0.25	0.41	0.43	1							
(15)	privacy	-0.07	0.02	0.12	0.2	0.36	1						
(16)	usefulness	0.28	0.14	0.23	-0.13	0.05	0.07	1					
(17)	understand	0.37	0.07	0.14	-0.11	-0.07	-0.06	0.52	1				
(18)	appr_setting	0.34	0.09	0.08	-0.19	-0.15	-0.04	0.64	0.5	1			
(19)	intention	0.34	0.17	0.1	-0.12	-0.12	-0.04	0.64	0.46	0.69	1		
(20)	accuracy	0.24	0.09	0.05	-0.13	-0.12	-0.08	0.26	0.33	0.25	0.29	1	
(21)	data_safety_1	0.14	0.03	0.04	0	-0.12	-0.22	0.11	0.3	0.2	0.18	0.21	1
(22)	data_safety_2	-0.15	0.03	0	0.01	0.13	0.19	-0.1	-0.09	-0.02	-0.13	-0.26	-0.11