MSc Programme in Urban Management and Development

Rotterdam, the Netherlands
August 2022

Gender and the Digital Divide:
Determinants in a Superdiverse Neighborhood of Rotterdam South

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Report number: 1687
UMD 18

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Summary

The digital divide could be considered a modern manifestation of social inequality, persistently relevant as the world continues to digitize. Study of the topic is widespread, with many reports on skill levels and digital usages, though typically on a regional or country level. For this study, the digital divide was conceptualized with four levels of access according to the model of Van Dijk: Motivation Access, Material Access, Skill Access, and Usage Access. Together, these concepts were measured as an index to determine an individual's digital inclusion. Understanding who can and cannot access, is or is not included, and therefore does or does not benefit from online services and information sources is imperative for development of digitally-focused policies and plans.

The lack of city-specific data for Rotterdam on this topic, combined with key characteristics like superdiversity of the population and national digital policies with local implications motivated the case selection. To execute this research, a survey was conducted in the Rotterdam district of Charlois, with a focus on the neighborhood of Carnisse to pilot the methodology for future, larger scale research. Beyond its functionality as a trial sample, Carnisse was selected due to its low social equality score relative to the rest of Rotterdam and explicit municipal interest in the area. Compounding factors of exclusion (i.e., low-income levels, foreign residents, social inequality) were central to the case study and analysis choices.

The primary objective of this research was to use intersectional methods to quantitatively analyze determinants of digital inclusion in the neighborhood of Carnisse. While focused specifically on gender, other individual-level determinants like age, education, income, nationality, and heritage were considered and compared as potential factors of digital inclusion. The interconnected nature of gender bias, ethnicity-based bias, and social exclusion was visible in the collected data and calculated econometric models.

Importantly, this thesis adds to a limited catalog of gender-focused digital divide studies. Applying an intersectional, gender-centered perspective of analysis to digital inclusion levels in Carnisse revealed differing exclusion factors for men and women, as well as lower digital inclusion levels for the non-Dutch population. Consequently, the findings outlined here have practical relevance for policymaking and encourage future deeper investigation regarding identity and digital inclusion.

Keywords

Digital divide, quantitative intersectionality, gender analysis, superdiversity, Oaxaca-Blinder Decomposition, stratified sampling

Acknowledgements

A heartfelt thank you to my colleagues involved in the data collection and feedback circles for this thesis—Carlos, Camilo, and Hussein, your support was invaluable both personally and academically. For the abundance of knowledge, your scholastic commitment, the formatting and late-night data entry assistance: I am grateful.

To friends, family, classmates, and my communities here in Rotterdam and in the US—learning from you and leaning on you made this work possible.

Finally, thank you to two instrumental professors—Dr. Beatriz Calzada Olvera for your guidance and recommendations regarding methodology, and Dr. Jan Fransen for instrumental feedback and overall encouragement. Your supervision and dedication to the success of this research is appreciated.

Foreword

This thesis was written as part of the study of an MSc in Urban Management and Development with a specialization in Urban Economic Development.

In addition to the academic and practical relevance of the digital divide, the selection of this topic and gender perspective were motivated by broader economic implications and themes. The effects of gender differences and consequential provision of targeted attention to digitally-disadvantaged groups have benefits beyond the immediate realm of the digital world. By addressing digital inclusion, related concerns like employability, economic participation, and financial inclusion are also confronted. The omnipresence of digitalization means that digital inclusion is a topic with broad applicability. Similarly, study of digital inclusion with explicit gender considerations fits within and contributes to a wider body of intersectional feminist research of economic-adjacent topics.

Abbreviations

CDO	Rotterdam Chief Digital Office
DESI	Digital Economy and Society Index
ICT	Information and Communication Technology
IHS	Institute for Housing and Urban Development Studies
NRI	Network Readiness Index
OB	Oaxaca-Blinder Decomposition

Table of Contents

List of Figures

List of Formulas

List of Graphs

List of Tables

List of Annex

1. Introduction

The Netherlands is an advanced welfare state where the majority of citizens have access to the internet and possess some level of digital skills (*DESI*, 2021); however, some communities are excluded from this progress. While the country is ranked 1st overall in the Network Readiness Index (NRI), it is ranked 7th in the sub-component of 'People' (Dutta & Lanvin, 2021). The NRI is concerned with digital technologies and their ability to reduce inequality; the lower 'People' score demonstrates a gap in how individuals, businesses, and government use ICT to participate in the Dutch network economy (Dutta & Lanvin, 2021). In an increasingly digitized world, some people will inevitably be left out of the advancement, unable to benefit from online information and services. This gap between people with and without material access, digital skills, usage opportunities, and their beneficial outcomes is referred to as the digital divide (van Dijk, 2017; van Dijk & Hacker, 2003). Crucially, these inequalities are relative, not absolute, and it is therefore still relevant to explore the case of the digital divide in a developed country, economy, and largely-digitized society (van Dijk, 2017).

Specifically in the Netherlands, with the Dutch Digitalization Strategy and a prioritization of digital skills and inclusion within the national agenda, it is useful to examine the divide that emerges as digitalization progresses (*DESI*, 2021). Knowledge of the digital divide status quo is important for individual Dutch cities acting under the guidance of national policies. The city of Rotterdam does not currently have a local digital inclusion strategy or coordinating set of programs; in order to create one, it is helpful to have city-level data about who is included or excluded, what skills they have and lack, and their perceptions about the digital realm.

In environments where other social stratifications already exist, the divide between the digitally included and excluded is particularly salient. Firstly, there is a sizable catalog of studies which recognize the link between Internet connectivity, economic success, and the social wellbeing of a population (Deichmann et al., 2006). It is also widely accepted that digital inequality reinforces existing social inequalities (van Dijk, 2017). In this research, the chosen reinforcing foci are gender inequality and intersectionality. More specifically, the perspective considers how varying identities such as gender, ethnic or national group, economic status, and other social positions combine and interact to create a heterogeneity of experience; 'intersectionality' is this combination of identities which result in a greater or lesser level of social power, and therefore of access and inclusion (Bauer et al., 2021; Crenshaw, 1989).

Intersectionality has long been used in qualitative research, but is a more recent addition to quantitative studies (Bauer et al., 2021). Specifically considering the digital divide, most research does not go beyond simple inclusion of gender as a potential determinant. While gender is present in preceding studies, the intersections and nuances of gender and identity are not deeply explored. The gender-centered approach, combined with existing commentary on social and digital divides, encourages this research, as the likelihood of a digital divide is often compounded by gender bias, discrimination, and exclusion in other societal realms.

Rotterdam in particular is an example of this concern. The city represents a sample of 'superdiversity', with new emerging identities and intersections between gender, socioeconomic status, and multi-generational migration backgrounds (Scholten, Crul, & van de Laar, 2019). In a place where visible diversity is both commonplace and increasingly part of 'normal' social contexts, where difference exists both amongst and between groups (Raco, 2018), mapping the digital gaps between Rotterdammers aligns with other concerns of access. Gender, identity, and the digital divide are intertwined similarly to how gender, identity, and their corresponding social capital affect accessibility to education, employment opportunities, healthcare, and networks.

This research is supported by the methodology and approaches used in identity-based exploration of other societal phenomena, that has only newly been applied to the digital divide. The interest and collaboration of the Rotterdam Chief Digital Office (CDO) also underscores the execution of this pilot research and data collection. To fit the scope and allotted time frame of this research, rather than collecting data covering the entirety of the city, the neighborhood of Carnisse in Rotterdam South was selected as the unit of analysis. It exemplifies key traits which indicate a potential digital divide, namely social inequality, diversity, and lower levels of income.

Throughout this thesis, the relationships between the digital divide, gender, and other identity variables are explored within the context of Carnisse. To do this, first, the concepts are explained through a literature review, thoroughly demonstrating the relevance of the topic. Subsequently, the research methodology is outlined and operationalized, with specific details about data instruments and analysis techniques. Following this are results and analysis, discussion of findings, and final conclusions.

1.1. Research Objectives

The central objective of this research is firstly to explore, in combination with gender, which factors are associated with being digitally included or excluded. Primary considerations are based on individual demographic traits like age, family composition, migration background, nationality, social integration, and perceived abilities in the context of the Carnisse case study.

Secondly, the research aims to understand more specifically the differences between women and men in skills, usage, and perceptions as related to digital inclusion. From the 'social power' focus of intersectionality, this objective addresses how gender and identity might influence self-perception, level of skills, most common digital uses, and thus the broader level of inclusion.

Finally, the research will analyze and compare men and women in Carnisse within the digital divide considering the context of a superdiverse city. It aims to define *who* exactly is digitally included or excluded, with a focus on gender, nationality, and heritage.

1.2. Research Questions

Based on the outlined objectives, this research will answer the subsequent questions:

> Q1: What are the determinants of digital inclusion for women compared to men in Rotterdam?
>
> Q2: In what ways are skills, usage, and perceptions about ability different between women and men?
>
> Q3: From an intersectional perspective, who is digitally excluded in Carnisse, considering gender and ethnicity in particular?

1.3. Research Scope

In sum, the research is focused on individuals and their characteristics which may explain the gap between digitally-included and digitally-excluded men and women in the studied neighborhood of Carnisse. Analysis of these factors will be conducted quantitatively. This thesis explores intersectionality and novel methodology with a small sample size in a highly diverse setting.

2. Literature Review

2.1 The Digital Divide, Gender Considerations, & Quantitative Analysis

Clear conceptualization of the digital divide is required to execute the implied analysis. Digital access can be studied as related to demographic factors, or, as a matter of social support, relationships, and categorical differences—essentially, by individual or group variables (van Dijk, 2017). For this research, data and analysis are based on individuals.

The divide between individuals in the digital realm is typically understood on three levels: material or physical access (first-level), skills and usage (second-level), and outcomes (third-level); the concept of 'outcomes' refers to who benefits the most from digital inclusion and how (Scheerder, van Deursen, & van Dijk, 2017; van Dijk, 2017). The first-level was the focus of most foundational digital divide literature; however, it is important to note that based on country-level data and the general development of the Netherlands, it is unlikely that a significant percentage of the population would be fully excluded in this way. Concerns for material access are still relevant though, because as technology develops, updated devices may be inaccessible to lower income groups (van Deursen & van Dijk, 2019). Also, different devices offer different benefits, e.g. smartphones offer a continual communication connection while desktop or laptop computers offer more advanced applications (van Deursen & van Dijk, 2019).

Moreover, the conceptualization of a second- and third-level divide adds more depth in a digitally-developed context. The third-level in particular assumes that even when citizens have near-full and near-equal access, as well as adequate skills, "there will be important differences in their proficiency in enlisting digital resources for the achievement of specific objectives"; social and information inequality can still persist because of the variation in digital skills and opportunities for usage (van Deursen & Helsper, 2015; van Deursen & van Dijk, 2020). Ultimately, the digital divide is more complex than a simple in or out status. There is a continuum of inclusion, where many people may have basic digital skills and sufficient material access, but lack the abilities and resources to fully benefit from digitalization (van Dijk, 2017).

The concept of digital access can also be broken down further. Van Dijk proposes four main types, elaborating beyond the previously described first-level access divide. Their model considers *motivational access* or attitudes towards the internet, *material access* or physical access to devices, internet connection, etc., *skills access* which can be medium related i.e. operational or content related i.e. information based, and *usage access* or time spent online and for what purpose (van Deursen & van Dijk, 2015; van Dijk, 2005). These access types advance understanding of how exclusion manifests in a population; by unbundling the concept of digital access, they outline and shape the factors that policies addressing digital inequality might consider. This conceptualization assumes a linear progression through the levels of access, which is likely more straightforward than the real-world phenomena. However, the access types are clearly distinct from each other, advance understanding of the topic, and are relatively easily measurable, therefore, they inform the structure, categorization, and usage of data within this research.

As previously explained, material access is largely extraneous in developed countries and economies such as the Netherlands. Most citizens have access to internet and the devices necessary to benefit from it (*DESI*, 2021). However, division still exists in the higher-tier categories of skills and usage.

The concept of skills access concerns an individual's digital or media literacy and can be subdivided into two types: medium-related and content-related skills (van Dijk, 2017). It is generally agreed that medium-related skills (i.e. how to use digital devices) are a prerequisite for other types of skill access which are more important, such as information retrieval, communication, and content creation (van Dijk, 2017).

Considering usage access, the types can be summarized in various categories. Some common clusters include: information seeking, news, personal development and education, leisure, commerce and transactions, social networking, and gaming–different uses are more common amongst different categories of people i.e. high/low-educated, young/old, or men/women (van Dijk, 2017). These usage categories are relevant to understanding how different people benefit or not from internet access, and to what extent they are included in digital opportunities.

Based on foundational literature, digital inclusion as categorized and outlined above can be partially explained through personal characteristics, and gender emerges as a potential explanatory factor. The earliest digital divide studies demonstrate a more significant effect of gender on exposure, attitudes, and as a consequence, on skills; particularly among younger women and girls, the differences in perceived abilities and comfort with technology between themselves and their male counterparts were pronounced in studies throughout the 1980s and 1990s (Cooper, 2006). Historically, computer efficacy, level of access, and level of usage across contexts has been lower for the poor, lesser educated, minorities, and women (Cooper, 2006; Hilbert, 2011). Over time, gender differences have diminished– but those that remain are more pronounced among marginalized groups, such as ethnic minorities (Hilbert, 2011). More recent self-reporting surveys also reveal a more pronounced gender difference than in practical skill tests, suggesting an ongoing effect of stereotypes on self-perception about abilities of men vs. women (van Deursen, van Dijk, & Peters, 2011). The concern for a self-perception bias for women is addressed in the analysis of the Carnisse case study.

While a Rotterdam-specific digital divide study has not been executed, country-level research in the Netherlands demonstrates varying conclusions on gender. Results showed that men typically have more positive attitudes towards technology, more stereotypical beliefs about its usage, and higher levels of usage due to work requirements; women typically have more digitally-related anxiety; men and women differ in their most common uses, with women using less often; overall, gender had a more indirect effect, most strongly affecting material access in the reviewed studies (van Deursen & van Dijk, 2015; van Deursen et al., 2011). Though varied across contexts in significance and effect, gender continually appears in some element of digital difference.

Beyond gender, digital access differences are "likely to have profound consequences, not least in the reinforcement of existing social inequalities" (Scheerder et al., 2017). Historic digital divide studies affirm that social capital affects an individual's ability to learn about the internet, different ways to use it, and to beneficially connect with others online (van Deursen & van Dijk, 2020). Digital advantage can bestow more social advantages, as well as the inverse (van Deursen & Helsper, 2015). The social inclusion implications of digital inclusion underpin the gender and intersectionality focus explained throughout this research.

While prior studies have highlighted the relevance of gender in a general way alongside other traits like age or education (van Dijk, 2006), studies specifically centered on exploring gender, intersectionality, and the digital divide are limited. To quantitatively analyze the digital divide from these perspectives, it is necessary to review the history and usage of them in other quantitative research. Though it is typically used qualitatively, an intersectionality and gender focus in quantitative analysis offers a deeper understanding of the cross-cutting roles of identity. Quantitative research is able to employ methodologies which uphold key tenets of intersectionality, like the multidimensionality and complexity of identity (J. Scott, 2010).

A recent German study used an intersectional approach to qualitatively investigate the effect of sociodemographic variables and multiple inequalities on the digital divide; the research used similar variables to those planned in this study but focused largely on digital users at home compared to the workplace (Ertl, Csanadi, & Tarnai, 2020). Other investigations into the digital divide that explicitly mention intersectionality are focused on healthcare or health information, which is more specific than this research scope (see Liu, 2021; Medero et al., 2022). In comparison, the broad NRI country-level study of digital inclusion examines the gender gap in internet usage specifically by calculating scores "as the ratio of the share related to the female population over the share related to the male population" (Dutta & Lanvin, 2021). This methodology is not explicitly intersectional, nor does it consider the wider picture of the digital divide, only usage. Other standard digital divide studies include gender analysis via variables in multiple regression, typically only gender but sometimes as an interaction term with age, for example (see: Lamberti, Lopez-Sintas, & Sukphan, 2021; van Deursen, van Dijk, & ten Klooster, 2015; van Dijk & Hacker, 2003).

Because of limited precedent for the specific lens and context proposed here, the methods and indicators employed by similar studies on comparable topics will be examined. As an overview, some common methodologies for intersectional quantitative research include: interaction terms, split-sample regressions, contextualized multiple regression, usage of latent variables, descriptive analysis, and multi-level modeling (Bauer et al., 2021; Codiroli Mcmaster & Cook, 2019; N. A. Scott & Siltanen, 2017). Most quantitative intersectional and gender-focused research employs more than one method of analysis to generate more robust results. Decomposition analysis is one method newly applied to intersectional studies to break-down and explain inequality (Bauer et al., 2021). To study the roles of gender and intersectionality most effectively in the digital divide, these indicators and methods are considered as guidance.

2.2 Literature Gaps & Academic Relevance

Two existing qualitative studies further encourage a quantitative exploration of digital divide and gender in the neighborhood of Carnisse. Firstly, a qualitative study conducted in Amsterdam studied intersectionality and how ICT reinforces existing inequities (Goedhart, Broerse, Kattouw, & Dedding, 2019). The study made important generational considerations, such as how a mother's knowledge affects children's ICT learning, interviewing mothers in Amsterdam with low socioeconomic position, considering their specific needs for digital skill improvement (Goedhart et al., 2019). Their findings about usage indicated that integration in digital society goes beyond provision of devices, also including considerations for language, simplicity of information available (on government websites, for example), and designing online services to be inclusive or accessible to the currently-excluded rather than simply teaching them how to use what already exists (Goedhart et al., 2019). The Amsterdam study was predicated on the concern that:

> "*very little is known about how already disadvantaged groups, in terms of gender, class or race, experience the digitalizing society, and use ICT in daily life, and what they need to participate in our digital society*" (Goedhart et al., 2019).

Similarly, this is the case in Rotterdam, with the additional consideration of a significant percentage of citizens with migrant backgrounds and lower socioeconomic standing. Since 2015, Rotterdam has been a majority-minority city (more than 50% of non-Dutch origin), with trends of polarization emerging between the second and third-generation migrants who do or do not move up in socioeconomic classes, and diversity within ethnic groups increasing over time (Scholten et al., 2019). Accordingly, conducting intersectional quantitative research in a similar context will address the gap found by the Amsterdam research.

A qualitative study in Spain further underscores the relevance of gender study and digital inclusion; this study found that employment status and care work limited available time for women to use the internet and improve their digital skills– long working hours plus the double burden of work at home left them feeling as though they had little time for internet use (Arroyo, 2020). Many women, especially the lower educated, did not use internet during their working hours, also affecting time spent online; however, all women in the study used the internet to help with their care tasks–looking for recipes, information and resources for children, or to communicate with family (Arroyo, 2020). Factors like employment, education, family responsibilities, and internet usage that were demonstrated qualitatively can also be measured quantitatively and then statistically evaluated in Carnisse.

These recent studies in Amsterdam and Spain align with other findings about gender throughout the historic, national-level analyses discussed Section 2.1. Results on gender are often inconsistent between contexts, further emphasizing the relevancy of considering an individual case study such as this one, while still acknowledging overarching significance. Academically speaking, this research is relevant and connected to existing knowledge, but offers additional insights due to its novelty in context and quantitative approach.

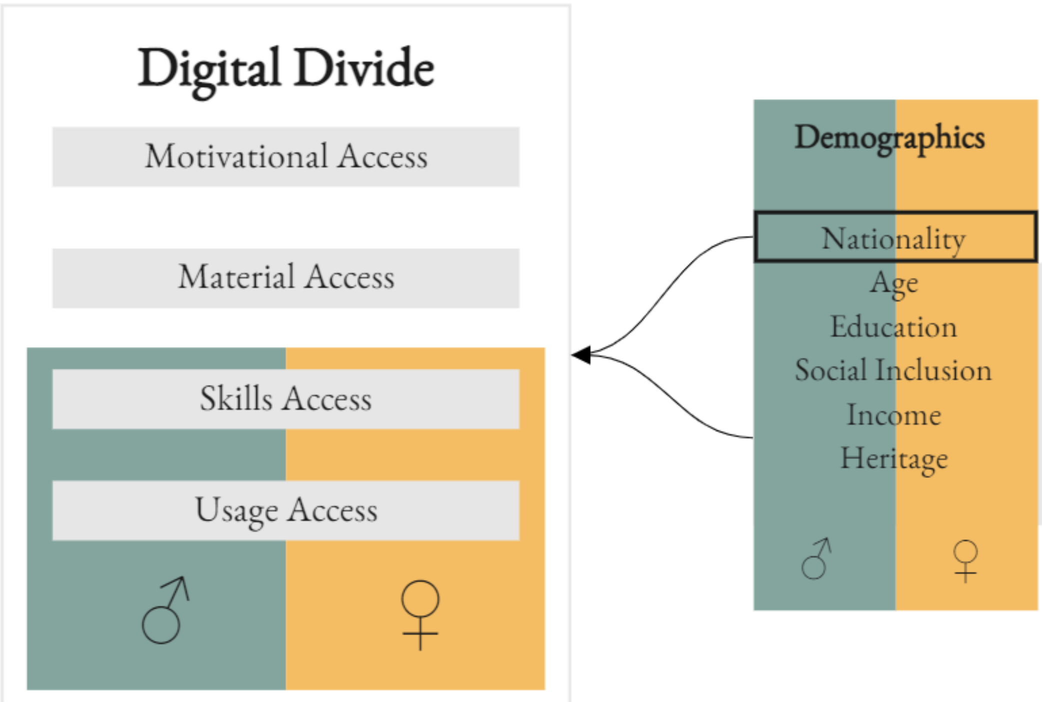
As outlined in the literature review, the chosen analysis perspective contributes strongly to existing literature on the digital divide. A key part of intersectionality is the context-specific nature of disadvantage– this also supports the execution of the Carnisse case study relative to using a higher-level unit of analysis, such as region or country. Evaluating Carnisse's digital divide with gender and intersectionality considerations adds to a limited catalog of digital divide studies with this focus. Mapping and quantifying the extent to which gender and intersectional identities in Carnisse explain digital inclusion or exclusion will enrich existing literature and address the gap in empirical evidence. The explicit lack of quantitative data on the current state of Rotterdam's digital divide also motivates the study. National statistics have been extrapolated to local level estimates, but no city-specific data exists on who is included or excluded, on what grounds, and their personal characteristics, skills, and motivations. Data collection and analysis on the digital divide in Carnisse or similar neighborhoods had not yet been done.

Finally, gender-focused studies in related disciplines consistently reveal differences between men and women. While female disadvantage has been historically measurable, the diminishing or even reversed gaps between men and women in developed economies (such as in educational attainment; see: Statistics Netherlands, 2019) has resulted in lesser focus on the topic in these contexts. Crucially, there are policy implications of gender differences even if individual outcomes are comparable, which makes the perspective continually relevant. While policy often aims to be neutral in treatment of gender and identity, in practice, its effects on marginalized groups are not neutral. Comparable considerations have been made by policymakers in regard to housing, education, and public administration (see: Hatch, 2022; Rauhaus & Schuchs Carr, 2022). Housing policies affect all people in the mandated area, but do not treat them the same due to sexist and racist legacies in policymaking (Hatch, 2022). This observation can be related to policy in other areas: though applied universally in the jurisdiction, individual impact will vary. Policy *is* capable, however, of considering gender in nuanced ways, such as through unconscious bias training, targeted skill instruction, or provision of childcare (Rauhaus & Schuchs Carr, 2022). In their example of public administration, Rauhaus and Schuchs Carr call the field "gender neutral at best", based on current mindsets, policies, research, and gender considerations (2022). This designation could also be applied to the status quo of the digital divide and its gender considerations based on the previously summarized literature, research, and methodologies. Consequently, in this research on Carnisse, differences between genders are studied with focus, aiming to advance knowledge which encourages development of gender-considerate digital policies.

2.3 Conceptual Framework

Based on the reviewed theory and planned research questions, the adopted research view is summarized in the following conceptual framework.

Figure 1. Conceptual Framework



Source: Author, 2022

3. Research Design & Methodology

This chapter will review the chosen research strategy, sample selection and calculation, concept operationalization and variable creation, and methodologies for data collection and analysis.

3.1 Research Strategy Overview

The purpose of this research is primarily exploratory. It aims to measure and describe the digital divide in the defined sample, then investigate how gender and identity influence digital inclusion or exclusion. In order to develop a picture of who is digitally included in Carnisse, on what, where, and why, this research collected basic data on aforementioned topics via survey. The survey was created to study the selected Rotterdam neighborhood which was more likely to be digitally excluded based on literature-proven traits, as explained in Section 3.2 Sample Selection. A survey was the proper instrument to conduct this research due to the large number of variables to be considered and the sufficiently large sample required to adequately summarize the digital divide. Achieving breadth of responses, particularly to study intersections of identity and their significance, was more central to this research than achieving depth. However, in constructing the survey, this limitation was balanced through inclusion of a wide range of relevant subjects, as outlined in the operationalization.

3.2 Sample Selection

Primary data was collected in Charlois (district in Rotterdam South), with a central focus on the neighborhood of Carnisse. Carnisse, and more widely Charlois, were selected for the data collection as a pilot plan to test the survey and analysis methodologies. This selection was based on two essential principles: neighborhood characteristics and adjacent projects.

Firstly, Carnisse is on average less socially-developed and poorer than the rest of Rotterdam. According to its Wijkprofiel ("Neighborhood Profile"), the 2021 population was 11,849 inhabitants in 59 hectares (2022). The relatively small population and area were also motivating factors; with the limitations of this research and available resources, it offered a relevant case without losing the viability of achieving a representative sample. Regarding social development, in 2022, Carnisse scored 62 on the city's subjective social index, which measures individual experience of quality of life, self-sustainability, co-reliance, participation, and perception of bond to the neighborhood (Municipality of Rotterdam, 2022). This was the 3rd lowest score for all Rotterdam neighborhoods; in 2020, Carnisse scored the lowest (Municipality of Rotterdam, 2022). As previously discussed, digital inequality and social inequality can reinforce each other, thus making Carnisse an interesting case study (van Dijk, 2017).

Furthermore, Carnisse has more households in the bottom 40% 'low-income group' of the national income distribution than the Rotterdam average (59% vs. 52%), and much fewer in the top 20% 'high income group' (6% vs. 16%) (Municipality of Rotterdam, 2022). Digital divide literature often includes income per capita as a determinant of exclusion; the higher concentrations of low- and middle-income individuals in Carnisse encourage its selection.
In terms of population composition, the idea of Rotterdam as a superdiverse city is visible in Carnisse. Carnisse has notably fewer non-migrant, native Dutch residents than Rotterdam as a whole (29% vs. 47%); there is also a higher concentration of Western background-migrants in Carnisse than in Rotterdam, many from Eastern Europe (31% vs. 14%) (Municipality of

Rotterdam, 2022). The number of non-Western migrants is comparable to the overall city level (Municipality of Rotterdam, 2022).

Finally, existing cooperation between the CDO and community associations prompted the selection. The CDO is currently creating a platform which improves social inclusion and connection in the neighborhood. The platform, ‘Wij Carnisse’, is being developed because of the previously outlined neighborhood traits and considers the digital division of residents in the area.

After neighborhood selection, the Yamane (1967) formula was used to calculate sample size:

$$n = N \, / \, (1 + N{*}e^2)$$

Formula 1. Yamane

Where n is the sample size, N is the total population and e is the marginal error. For this research, a marginal error of 10% was calculated, considering the described limitations of data collection and sufficiency of a 90% confidence level for the research aims. Thus, the sample size was determined using Equation 1 as follows:

$$n = 11{,}849 \, / \, (1 + 11{,}849 * 0.1 * 0.1)$$
$$n = 11{,}849 \, / \, 119.49$$
$$n = 99.16 \cong 100$$

Due to the econometric analysis intended by this research, the sample also had to meet the basic assumptions of selected models. Based on this necessity and the assumption that some responses would be incomplete due to paper-based collection method, more data was collected than statistically required to improve representativity and robustness. In total, 187 responses were collected, surpassing the minimum calculated threshold of 100.

3.3 Operationalization

Based on the summarized literature, the exploratory aims of the CDO, and existing digital divide surveys, variables within the study were operationalized as follows.

Primary dependent variable: Digital Inclusion
The dependent variable is a created index, compiled from indicators within the Operationalization Table (See below: Motivational Access, Material Access, Usage Access, and five ‘Skills’ categories). Further explanation of the index creation and reasoning is outlined in Section 3.5 Data Analysis Techniques. The four sub-indices are also used as secondary dependent variables in various analytical models to show greater detail. Each was operationalized separately and compiled to make the overall Digital Inclusion index, in alignment with the four levels of access which guided this research (van Deursen & van Dijk, 2015; van Dijk, 2005).

Secondary dependent variable: Motivational Access
Motivational access considers attitude towards and interest in using the internet (van Deursen & van Dijk, 2015; van Dijk, 2005). For this research, attitudes were measured with two statements of agreement or disagreement about how access to internet and digital devices improves the individual’s life and their feeling that their knowledge has increased because of

the internet. An additional question was asked about stress and anxiety level related to using digital devices and/or the internet, as this also influences motivation and use patterns (van Deursen & van Dijk, 2015).

Secondary dependent variable: Material Access
Material access is defined here as access to internet and the necessary devices to connect to and benefit from the internet (van Deursen & van Dijk, 2019). While physical access is near-universal in a developed country like the Netherlands, there are still considerations for what types of devices a person may have and what benefits each (van Deursen & van Dijk, 2019). Consequently, types of devices were weighted differently within the index. Regarding internet, questions covered access to connection at home and in other locations to better understand material access patterns, especially in the case that an individual responded 'no' to connection at home.

Secondary dependent variable: Skills Access
Skills access studies the necessary skills required to use the internet effectively and efficiently; it considers both medium-related skills (operational) and content-related skills (van Deursen & van Dijk, 2015). Skills were measured and categorized based on a combination of the research of van Deursen, Helsper, and Eynon (2014) and Ferrari (2012). A Likert scale with statements and answers based on truth claims (i.e., 'not at all true of me' or 'very true of me') was the primary response format selected; only Operational Skills were included as yes or no questions, rather than a range of ability. The chosen skill statements were adapted from the 'From Digital Skills to Tangible Outcomes' project report (van Deursen et al., 2014).

Secondary dependent variable: Usage Access
Actual usage is the final piece of access, considering what types of activities are performed online and with what frequency (van Deursen & van Dijk, 2015; van Dijk, 2005). The usage type categories and questions were informed by best-practice literature for survey creation and findings from studies comparing the usage by gender outlined in Chapter 2 (Helsper, van Deursen, & Eynon, 2016; van Dijk, 2017). Questions about usage frequency differentiated between internet and software/applications in order to garner more detail about the potential usage gap (Scheerder et al., 2017). Email was included as a yes or no type of usage based on its relevancy to accessing many digital services, per the interest of the CDO.

Independent variables: Demographic Characteristics, Migration & National Identity, Social Inclusion, Stereotype Perception
This research focuses on personal factors like age, education, income, gender, and ethnic identity, with questions that also consider social inclusion and stereotype perceptions.

Regarding ethnic identity, the survey asked a set of questions, rather than just one, in order to better map the superdiversity of Rotterdam. Respondents were asked their nationality, parents' places of birth, and native language. Because many of Rotterdam's residents are second or third generation migrants, the additional question about parental heritage illuminates groups which have Dutch nationality but a different cultural background or an intersection of ethnic identities, and may experience minority biases (Scholten et al., 2019).

To measure social inclusion, a known correlate to digital inclusion, respondents were asked to rate on a Likert scale their level of community participation and perception of social consideration (Scheerder et al., 2017). These responses were then compiled into an index as follows.

Table 1. Index: Social Inclusion

Index: Social Inclusion	
Components	Component Weight
Level of participation in community (scale 1-5)	0.5
Perception that social needs, problems, and personal circumstances are considered by the municipality (scale 1-5)	0.5

Source: Author, 2022

To measure stereotype perception, respondents were asked to rate on a Likert scale their beliefs about and personal experiences with stereotypes about gender and ethnicity, both widely and specifically regarding digital usage or abilities. These variables were combined in two separate variables, one combining all seven stereotype questions, and the other focused only on digital stereotypes. Both are indices with values between 0 and 1.

Table 2. Index: Stereotype Perception

Index: Stereotype Perception	
Components	Component Weight
Belief in stereotypes in general based on identity	14%
Personal experience of stereotypes in daily life	14%
Personal experience of stereotypes in work or education	14%
Belief in stereotypes about digital usage/skills and gender	14%
Personal experience of stereotypes about digital usage/skills and gender	14%
Belief in stereotypes about digital usage/skills and ethnicity	14%
Personal experience of stereotypes about digital usage/skills and ethnicity	14%

Source: Author, 2022

Table 3. Index: Digital Stereotype Perception

Index: Digital Stereotype Perception	
Components	Component Weight
Belief in stereotypes about digital usage/skills and gender	0.25
Personal experience of stereotypes about digital usage/skills and gender	0.25
Belief in stereotypes about digital usage/skills and ethnicity	0.25
Personal experience of stereotypes about digital usage/skills and ethnicity	0.25

Source: Author, 2022

The following table summarizes key concepts and indicators operationalized for the research. It considers the selected dependent variable, its subcomponents, as well as the outlined independent variables and other concepts measured by the data collection.

Table 4. Operationalization

Concept	Indicators	Data Type	
Social Inclusion	Community participation	Categorical 1-5	Ordinal
	Social needs/problems/circumstances considered by Municipality	Categorical 1-5	
Perception of Stereotypes	Existence of stereotypes	Categorical 1-5	Ordinal
	Daily personal experience of stereotypes	Categorical 1-5	
	Daily work/educ experience of stereotypes	Categorical 1-5	
	Existence of stereotypes - digital + gender	Categorical 1-5	
	Digital + gender stereotypes personal experience	Categorical 1-5	
	Existence of stereotypes - digital + ethnicity	Categorical 1-5	
	Digital + ethnicity stereotypes personal experience	Categorical 1-5	
Material Access	Types of devices at home	Binary	
	Number of devices at home	Continuous	
	Access to internet at home	Binary	
	Access to internet at other locations (home, work/school, traveling, other)	Binary	
Usage Access	Email address	Binary	
	Frequency of internet usage	Categorical 1-6	Ordinal
	Frequency of application/software usage	Categorical 1-6	
	Types of usage (media, gaming, leisure search, practical search, online course, news, job search, online shopping, product reviews, social networks, sharing photos/videos, other)	Binary	
Operational Skills	Connect to wifi	Binary	
	Look for info with search engine	Binary	
	Install apps on mobile device	Binary	
	Download and retrieve files	Binary	
	Attach file to email	Binary	
	Complete online forms	Binary	
	Avoid computer viruses	Binary	
Information Seeking Skills	Deciding best keywords for online search	Categorical 1-5	Ordinal
	Navigating websites	Categorical 1-5	
Software & Content Creation Skills	Change settings on device/application	Categorical 1-5	Ordinal
	Find, download, install, configure applications	Categorical 1-5	
	Produce or edit content with word processor	Categorical 1-5	
	Produce or edit spreadsheets	Categorical 1-5	
	Use basic formulas in a spreadsheet	Categorical 1-5	
	Create digital presentations	Categorical 1-5	
	Produce or edit simple digital content (images, video, audio)	Categorical 1-5	
	Use specific software for design, calculation, and/or simulation	Categorical 1-5	
Safety & Security Skills	Check if information and websites are trustworthy	Categorical 1-5	Ordinal
	Know which information should/should not share online	Categorical 1-5	
	Feel safe sharing information online for municipal services, subscriptions, etc.	Categorical 1-5	
Problem-Solving Skills	Ability to solve routine problems with devices	Categorical 1-5	Ordinal
	Ability to find support/assistance when problem occurs	Categorical 1-5	
Digital Inclusion	Compared to others, personal skill level with digital devices and/or the internet is (personal perception)	Categorical 1-5	Ordinal
	Has a DigID	Binary	
	Has used DigID to access services in prev. 12 months	Binary	
Motivation Access	Level of stress/anxiety using digital devices and/or the internet	Categorical 1-5	Ordinal
	Belief that access to internet/digital devices has improved personal life	Categorical 1-5	
	Belief that personal knowledge has increased because of the internet	Categorical 1-5	
Characteristics	Average household gross monthly income (prev. 12 months)	Categorical 1-10	Ordinal
	Employment status	Categorical 1-7	Nominal
	Employment contract type	Categorical 1-3	
	Employment sector	Categorical 1-12	
	Occupation	Categorical 1-8	
	Age	Continuous	
	Gender	Categorical 1-4	Nominal
	Number of kids under 18 in household	Continuous	
	Education	Categorical 1-5	Nominal
	Zipcode	String (text)	
Migration & National Identity	Nationality	String (text)	
	Parents' countries of birth	String (text)	
	Native language	String (text)	
	Fluency in Dutch	Categorical 1-4	Ordinal
	Fluency in English	Categorical 1-4	Ordinal
Digital Skill Improvement Service Preferences	Preferred format	Categorical 1-2	Nominal
	Preferred assistance type	Categorical 1-4	
	Preferred location	Categorical 1-5	
	Preferred days of week	Categorical 1-2	
	Preferred time	Categorical 1-5	

Source: Author, 2022

3.4 Data Collection Method

The data collection was conducted via physical distribution of a paper survey. Because of the topic and objective of reaching digitally-excluded citizens, paper distribution was selected in place of digitally disseminating the survey. The survey was available in four languages (English, Dutch, Polish, Turkish) to accommodate more diverse responses. Responses were collected in public spaces, community meeting centers, stores, restaurants, libraries, as well as door-to-door within the neighborhood of Carnisse. Community volunteers and involved residents were instrumental in providing suggestions to access to the targeted group; two important and recommended locations for reaching respondents were KOCO and the Amelandsplein Park. KOCO is a community center focused on educating residents to better assimilate into the labor market that also serves as a meeting place, restaurant, and residence for the elderly. The park is a central meeting place for neighborhood residents that attracts a diverse cross-section of people. Due to the comprehensive nature of the survey, the requirement of sufficiently diverse ages and identities of respondents, and the distribution method, respondents included both residents of Carnisse, of Charlois more widely, and people present in the neighborhood at the time of data collection. Therefore, the sample is representative of Carnisse and the surrounding areas as intended.

The survey itself was a self-reported evaluation of skills, usage, motivation, and access from selected respondents. It contained eight sub-sections; for this research, the categories of interest were: 1. Social Perceptions, 2. Material Access, 3. Digital Usage, 4. Digital Skills, and 5. General Demographic Information. Section 1 asked respondents to evaluate personal perceptions and experiences of social inclusion and stereotypes. Sections 2 through 4 were designed to measure the four levels of digital access as conceptualized by Van Dijk through yes/no, Likert scale, and multiple choice questions. Further detail about each section is outlined in the operationalization table.

The survey creation and data collection were executed by the IHS student working group with guidance from the CDO, and thus also included sub-sections on Financial Inclusion, Labor Market, and Municipal Services to be used for adjacent research projects. Data was collected over a period of three weeks in June 2022 in the selected district and neighborhood, then analyzed quantitatively according to a planned methodology.

3.5 Data Analysis Techniques

As stated, the primary dependent variable is ‘Digital Inclusion’, as measured by an index created from survey data. To create the index summarizing an individual’s digital inclusion or exclusion, each of the four levels of the digital divide as conceptualized by Van Dijk (Motivational Access, Material Access, Skills Access, Usage Access) were measured through a series of sub-questions and concepts seen in the operationalization table. Each of the four access types was bundled into an index based on the number of complete observations; only those with sufficient complete responses were included in these composites. Cronbach’s Alpha was also used to ensure that the variables composing each sub-index were internally consistent and reliable, effectively measuring the target concept (Ursachi, Horodnic, & Zait, 2015). The majority of composites scored above the required 0.6 minimum threshold; of which, most scored above the preferred 0.8 value. If the Cronbach’s Alpha was insufficiently high, existing literature on the digital divide was considered sufficient grounds to combine sub-questions into one index. This resulted in four indices for the four types of access.

Subsequently, each of the four access indices (Motivational, Material, Usage, and Skills) were equally weighted to create the final Digital Inclusion Index. The final variable (as well as each sub-component) is an index from 0 to 1 measuring someone's digital inclusion or abilities, with 0 being 'fully excluded' and 1 being 'fully included' for the purposes of this research. The following tables summarize the index creation.

Table 5. Creation of Indices

Index: Motivation Access	
Components	Component Weight
Belief that access to internet and digital devices has improved respondents' life (scale 1-5)	0.5
Knowledge has increased because of the internet (scale 1-5)	0.5

Index: Material Access	
Components	Component Weight
Has computer (yes/no)	0.4
Has reliable access to internet (yes/no)	0.4
Has smartphone (yes/no)	0.1
Has tablet (yes/no)	0.1

Index: Skill Access	
Components	Component Weight
Operational skills (7 sub-questions, yes/no)	0.32
Information seeking skills (2 sub-questions, scale 1-5)	0.09
Software and content creation skills (8 sub-questions, scale 1-5)	0.36
Safety and security skills (3 sub-questions, scale 1-5)	0.14
Problem solving skills (2 sub-questions, scale 1-5)	0.09

Index: Usage Access	
Components	Component Weight
Has email address (yes/no)	0.25
How often do you use the internet? (scale 0-5)	0.25
How often do you use online software or applications? (scale 0-5)	0.25
Types of usage (from 0 to 12 types; each type weighted 0.02)	0.25

Index: Digital Inclusion	
Components	Component Weight
Material Access Index	0.25
Motivation Access Index	0.25
Skill Access Index	0.25
Usage Access Index	0.25

Source: Author, 2022

To analyze the index, statistical methodologies were informed by prior digital divide research, studies in adjacent social sciences, and academic literature on quantitative intersectional analysis more generally (see: Else-Quest & Hyde, 2016a, 2016b; Jann, 2008; N. A. Scott & Siltanen, 2017; Vehovar, Sicherl, Hüsing, & Dolnicar, 2006).

The following methods were employed to answer the outlined research questions:

I. Multiple regression
II. Multiple regression using stratified samples
III. Summary statistical analysis
IV. Oaxaca-Blinder Decomposition

All selected models focus on demographic and personal characteristics of individual respondents with an emphasis on gender and ethnic identity. As explained in the literature review and academic relevance sections, this addresses a current gap in digital divide studies.

I. Multiple regression

OLS multiple regression analysis was conducted on the entire sample to establish a baseline of trends and compare to common factors of inclusion and exclusion as defined by literature.

II. Multiple regression with stratified samples

Conducting multiple regression on stratified samples allows modeling of differences between men and women, incorporating the nuances of identity which impact digital inclusion. Different factors influence digital inclusion for the total sample vs. the stratified samples. When further analyzing the four sub-components of the digital inclusion index via multiple regression, a similar conclusion is reached. While these stratified multiple regression models add depth to gender analysis that a whole sample analysis ignores, they also induce an imbalance between the split samples (difference in number of observations, difference in mean values for independent variables, etc.) and thus a resulting loss of information from dividing the dataset. Therefore, additional methods are employed.

III. Summary statistical analysis

To offset limitations of the stratified samples and garner a more robust finding on differences between groups, investigation into summary statistics is utilized to study gender, ethnicity, skills, usage, and self-perceptions.

IV. Oaxaca-Blinder Decomposition

Using the Oaxaca-Blinder Decomposition (OB) method, further information on group differences in digital inclusion is revealed. Specifically, a twofold OB decomposition model was employed in this study. This method splits the differential of Digital Inclusion scores between the selected groups (reference group = 0 and focal group = 1) into a residual that is explained by included independent variables, and a residual that *cannot* be accounted for with the included characteristics. The difference that is *unexplained* by age, education, income, etc. (the included, observed demographic characteristics) is understood to be caused by a combination of unobserved variables and an immeasurable "discrimination effect" (Jann, 2008). The twofold OB provides a variable-by-variable explanation of what influences or does not influence between-group difference. This type of analysis is often used to study the gender wage gap and instances of racial disparity in education, for example (Jann, 2008). Applied here, it further describes the roles of gender and ethnic identity in understanding the digital divide.

Qualitative analysis of concepts like intersectionality or superdiversity has demonstrated that difference is expected, but not necessarily measurable by basic or common statistical methods. This research attempts to address that by using multiple quantitative analyses and integrating their results to create a fuller picture. Synthesizing the results of these techniques suggests that simply considering gender or ethnic background in a typical multiple regression model does not fully represent its impact. Stratifying the sample based on known identity categories, more closely measuring between group differences with OB decompositions, and comparing averages across identity categories offers deeper conclusions.

3.6 Methodological Validity & Reliability

General limitations include sample size and the inability of statistical models to fully measure or capture the nuanced intersections of identity in the same way that qualitative analysis does. Further analysis using multilevel modeling of non-nested categories (gender and ethnicity) would likely add more depth to the findings but was not feasible in this research due to previously explained limitations, namely sample size.

With the Oaxaca-Blinder Decomposition specifically, limitations include the model's inability to consider "premarket" discrimination in areas like education and income; the survey data for these variables may be impacted by pre-existing discrimination in the workplace or societal mindsets that lead to a starting lower value for women or minorities (Jann, 2008). The OB cannot count this and may thus underestimate the difference between groups. Alternatively, the difference between groups may be overestimated as a result of excluded or unobserved variables.

4. Results & Analysis

Chapter 4 examines and analyzes the collected data. Section 4.1 describes in detail the dataset which resulted from survey responses. Section 4.2 sets the baseline assumption of how gender informs the digital divide, using methodology typically employed by digital divide research. Sections 4.3, 4.4, and 4.5 study the outlined research question and sub-questions through the intersectional perspective adopted by this research.

4.1 Data Description

Dependent Variables:
Regarding the Digital Inclusion index and its sub-indices, the variation within means and standard deviations is of note. As expected per literature, the Material Access mean is highest with a value of 0.884; this suggests that as anticipated, most of the surveyed population have access to digital devices and the internet.

While the mean Digital Inclusion score is 0.830, the two subcomponents of Skill Access and Usage Access have lower means. Of the sub-indices, Skill Access is the most varied between respondents, but Usage Access is least varied. Because of missing responses (either non-responses, or response of "I don't know"/ "Not Applicable"), the number of observations varies between the indices.

Table 6. Summary Statistics - Indices

Index	Obs	Min	Max	Mean	Std. Dev.
Motivation Access	167	0.200	1	0.804	0.215
Material Access	178	0	1	0.884	0.204
Skill Access	180	0.136	1	0.763	0.224
Usage Access	178	0.021	1	0.769	0.158
Digital Inclusion	152	0.367	0.995	0.830	0.126

Source: Author, 2022

Independent Variables:
The following table displays the summary statistics for the independent variables, both considering the whole sample and the averages for men and women separately.

Table 7. Summary Statistics - Independent Variables

Independent Variables	Description	Obs	Mean	Std. Dev.	Female Mean	Male Mean	Min	Max
age	Age of respondent	181	38.87	15.02	38.53	39.28	18	99
curacao_hert	Either mother or father is from Curacao	187	0.04	0.19	0.05	0.02	0	1
educ	Education level of respondent (categorical)	177	2.91	1.02	2.89	2.94	1	5
employed	Respondent is employed either part or full time	187	0.51	0.50	0.45	0.57	0	1
eucitizen	Nationality from EU country excluding Netherlands	187	0.11	0.31	0.15	0.06	0	1
female	Variable = 1 if respondent is female	187	0.53	0.50	-	-	0	1
income	Income of respondent (categorical)	162	4.99	3.19	4.38	5.73	1	10
kids	Number of children under 18 living in respondent's household	178	1.09	1.23	1.08	1.10	0	5
morocco_hert	Either mother or father is from Morocco	187	0.05	0.21	0.05	0.05	0	1
morocco_natl	Respondent nationality = Moroccan	187	0.03	0.16	0.03	0.02	0	1
nondutch_self	Variable = 1 if respondent nationality is NOT Dutch	187	0.39	0.49	0.37	0.40	0	1
nondutchparent	Variable = 1 if respondent mother or father is NOT Dutch	187	0.75	0.43	0.76	0.75	0	1
nonnativedutch_speak	Variable = 1 if respondent's native language is NOT Dutch	187	0.57	0.50	0.57	0.57	0	1
pakistan_hert	Either mother or father is from Pakistan	187	0.06	0.24	0.01	0.11	0	1
poland_natl	Respondent nationality = Polish	187	0.05	0.21	0.06	0.03	0	1
soc_incl	Index of social inclusion score	152	0.60	0.22	0.59	0.62	0.2	1
stereotypes	Composite perception of stereotypes	126	0.53	0.19	0.53	0.53	0.2	1
st_digital	Composite perception of stereotypes about digital usage	131	0.47	0.22	0.47	0.48	0.2	1
suriname_hert	Either mother or father is from Suriname	187	0.07	0.26	0.11	0.03	0	1
turkey_hert	Either mother or father is from Turkey	187	0.10	0.30	0.07	0.13	0	1
turkey_natl	Respondent nationality = Turkish	187	0.05	0.23	0.02	0.09	0	1

Source: Author, 2022

Most variables used within the research are binary variables representing identity groups; other demographic variables like age, income, education, and employment status are also used. In the survey, the question on gender gave respondents four options: male, female, other, prefer not to say. In practice, all respondents selected male, female, or skipped the question entirely. Consequently, ‘female’ was coded as a binary variable. The categorical variables of education and income were split and represented as follows.

Table 8. Education

Value	Education	Obs	Percentage
1	Primary Education	13	7%
2	Secondary Education	46	26%
3	Bachelor's Degree - Vocational	78	44%
4	Bachelor's Degree - Academic	24	14%
5	Master's Degree or higher	16	9%

Source: Author, 2022

The most common education levels were secondary and vocational bachelor’s degrees, comprising 70% of the sample. While education is spread throughout the categories, it can be said that highly-educated respondents are a minority.

Table 9. Income

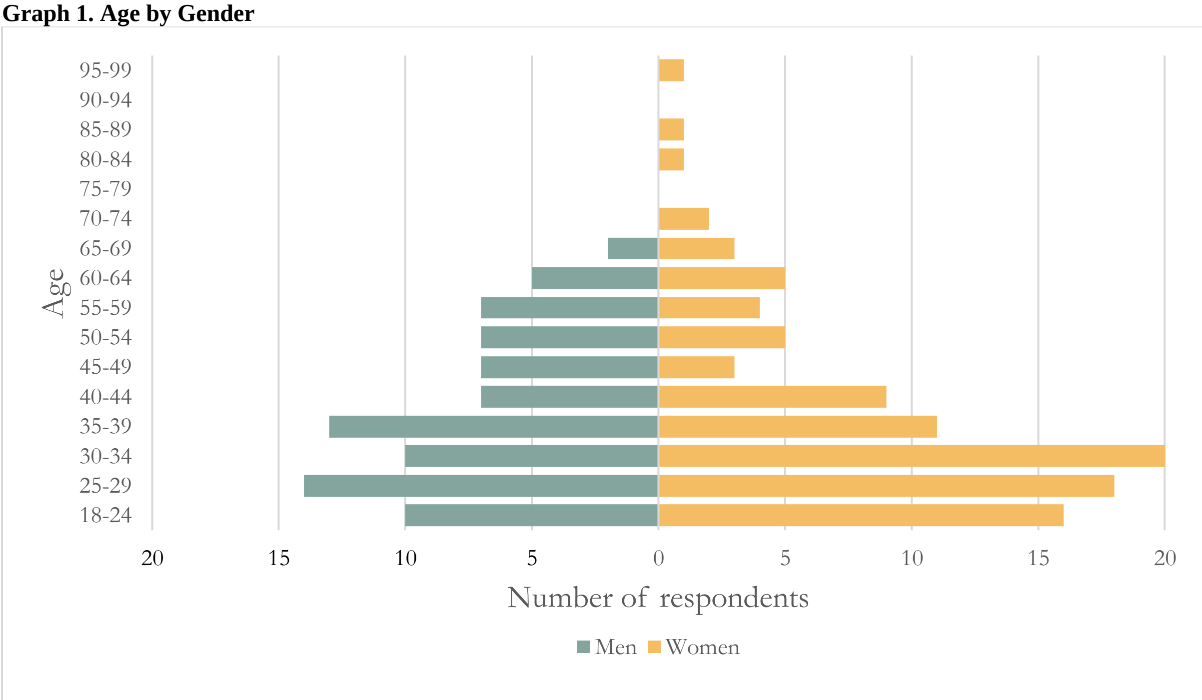
Value	Income	Obs	Percentage
1	€1350 or less	26	16%
2	€1350 - €1850	20	12%
3	€1851 - €2350	21	13%
4	€2351 - €2850	19	12%
5	€2851 - €3350	10	6%
6	€3351 - €3850	14	9%
7	€3851 - €4350	10	6%
8	€4351 - €4850	7	4%
9	€4851 - €5350	6	4%
10	more than €5350	29	18%

Source: Author, 2022

More than half (53%) of respondents had an income at or below €2850, this fits with the expected neighborhood values for number of low-income households. Interestingly, the individual category with the most observations was the highest level of 'more than €5350'. This is a higher percentage than expected based on the Carnisse profile outlined in Chapter 3 but could be attributable to individuals which live in the larger district of Charlois as explained by the sampling methodology and is comparable to the level for all of Rotterdam.

A further breakdown of age and education by gender was also considered, as these are often key factors in explaining the digital divide (*DESI*, 2021).

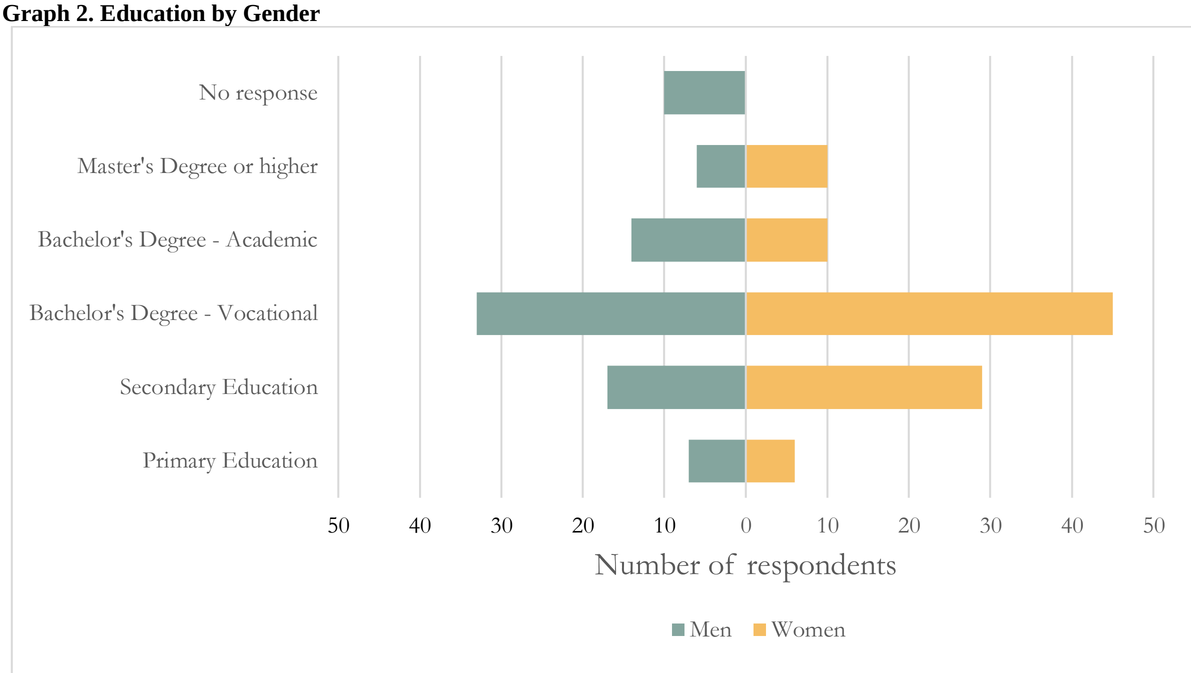
Graph 1. Age by Gender



Source: Author, 2022

Most of the respondents are between the ages of 20 and 40, split fairly equally by gender, but all observations over the age of 70 are women. When considering how age may impact the digital divide, this is a notable facet of the data.

Graph 2. Education by Gender



Source: Author, 2022

Considering education, a noticeably larger percentage of women have only secondary education; more men have achieved an academic bachelor's degree. All non-respondents were male.

To further analyze diversity, the most listed parental countries of origin and individual nationalities were created as separate variables.

Table 10. Heritage and Nationality

Identity	Women	Men	Total Respondents
Curacao heritage	5	2	7
Turkey heritage	7	11	18
Morocco heritage	5	4	9
Suriname heritage	11	3	14
Pakistan heritage	1	10	11
Turkey nationality	2	8	10
Morocco nationality	3	2	5
Poland nationality	6	3	9
EU nationality (excluding Dutch)	15	5	20
Dutch nationality	63	52	115

Source: Author, 2022

The five heritage variables represent the most frequently listed parent places of birth (heritage), out of a total of 43 unique countries of origin. The five nationality variables represent the most frequently listed nationalities, out of a total of 23 unique nationalities. Within the 20 non-Dutch EU citizens, there are 9 different countries; however, they were combined to capture a potential effect of presumed similar legal status in terms of right-to-work. Overall, there were 80 respondents (39%) with non-Dutch nationality. Furthermore, 149 respondents (75%) had at least one parent born outside the Netherlands. 115 respondents (57%) listed their native language as not Dutch. Between these respondents, 36 unique native languages were listed. In sum, regarding identity, the dataset clearly captured the superdiversity of Rotterdam and specifically Carnisse.

When distribution of age, gender, education, income, and other relevant variables are considered, the database has a balanced set of observations suitable for econometric analysis.

4.2 Establishing the Role of Gender as a Determinant

The first step for this research is to determine if, within the sample, gender is a determinant of digital inclusion, as typically conducted in digital divide studies. Here, in multiple regression analysis of whole-sample data, *it is not*. Methodological literature suggests both usage of an index and a logarithmic transformation for measuring the digital divide (Vehovar et al., 2006); in the lin-lin and log-lin models, the significant variables are consistent. In all models, when the variable 'female' is considered as a potential determinant of the Digital Inclusion index score, as well as the sub-components, it is *not* significant in explaining inclusion or levels of access. Detailed results are visible in Annex 1 and 2.

However, when considering a gender-stratified sample, it is clear that the determinants of digital inclusion and the subcomponents of access *are* different for men and women, even if gender itself is not significant in explaining digital inclusion or its subcomponents. This difference in regression outputs for just men vs. just women indicates that gender does have some effect that is not captured when incorporated only as a regressor in an OLS model.

4.3 Digital Inclusion Separated by Gender

Q1: What are the determinants of digital inclusion for women compared to men in Rotterdam?
To study gender difference as implied by Q1, the research employed multiple analysis methods. First, multiple regression models were conducted on stratified samples of male and female respondents. Key factors such as age, education, and social inclusion found to be relevant in other contexts were studied here for their individual impacts on women compared to men. The same eight models were conducted for both groups, Models 1-8 F and M, respectively.

Table 11. Models 1 - 4 F

	(1F)	(2F)	(3F)	(4F)
Digital Inclusion Index	**Model 1F**	**Model 2F**	**Model 3F**	**Model 4F**
age	-0.00157	-0.00186	-0.00210	-0.00197
	(0.00107)	(0.00111)	(0.00120)	(0.00115)
income	0.00710*	0.00612	0.00418	0.00453
	(0.00307)	(0.00309)	(0.00338)	(0.00360)
educ	0.0480***	0.0479***	0.0416***	0.0413***
	(0.0111)	(0.0114)	(0.0109)	(0.0108)
nondutch_self		-0.0310	-0.0485	-0.0531
		(0.0234)	(0.0248)	(0.0266)
soc_incl			0.0497	0.0475
			(0.0519)	(0.0523)
nondutchparent				0.0207
				(0.0307)
_cons	0.720***	0.747***	0.763***	0.744***
	(0.0496)	(0.0566)	(0.0530)	(0.0573)
N	77	77	62	62
R^2	0.277	0.294	0.262	0.268
adj. R^2	0.248	0.255	0.196	0.188

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: Author, 2022

Table 12. Models 1 - 4 M

	(1M)	(2M)	(3M)	(4M)
Digital Inclusion Index	**Model 1M**	**Model 2M**	**Model 3M**	**Model 4M**
age	-0.00130	-0.00227*	-0.00275**	-0.00275**
	(0.00116)	(0.000988)	(0.00100)	(0.00102)
income	0.00774	0.00193	0.00226	0.00228
	(0.00537)	(0.00579)	(0.00632)	(0.00630)
educ	0.0382	0.0485*	0.0280	0.0280
	(0.0223)	(0.0205)	(0.0222)	(0.0224)
nondutch_self		-0.127**	-0.0913*	-0.0916*
		(0.0366)	(0.0398)	(0.0452)
soc_incl			0.0301	0.0304
			(0.0687)	(0.0704)
nondutchparent				0.000879
				(0.0264)
_cons	0.724***	0.814***	0.876***	0.876***
	(0.106)	(0.0757)	(0.0773)	(0.0792)
N	59	59	52	52
R^2	0.199	0.400	0.283	0.283
adj. R^2	0.155	0.355	0.205	0.188

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: Author, 2022

Table 13. Models 5 - 8 F

	(5F)	(6F)	(7F)	(8F)
Digital Inclusion Index	**Model 5F**	**Model 6F**	**Model 7F**	**Model 8F**
age	-0.00197*	-0.00161	-0.00230*	-0.00187
	(0.00115)	(0.00109)	(0.00125)	(0.00120)
income	0.00453	0.00476	0.00347	0.00384
	(0.00360)	(0.00377)	(0.00352)	(0.00353)
educ	0.0413***	0.0321***	0.0429***	0.0324**
	(0.0108)	(0.0109)	(0.0117)	(0.0124)
soc_incl	0.0475	0.0702	0.0758	0.0954
	(0.0523)	(0.0525)	(0.0594)	(0.0572)
nondutch_self	-0.0531*		-0.0606**	
	(0.0266)		(0.0272)	
nondutchparent	0.0207	0.0195		
	(0.0307)	(0.0300)		
turkey_natl		-0.115***		-0.0828**
		(0.0277)		(0.0333)
morocco_natl		-0.0427		-0.0768***
		(0.0255)		(0.0135)
eucitizen_exdutch		-0.0878*		-0.101*
		(0.0477)		(0.0504)
curacao_hert			-0.0866	-0.0823
			(0.0527)	(0.0534)
morocco_hert			0.0241	0.0378**
			(0.0179)	(0.0168)
suriname_hert			-0.0263	-0.0216
			(0.0393)	(0.0362)
turkey_hert			-0.0469*	-0.0435*
			(0.0275)	(0.0253)
pakistan_hert			0	0
			(.)	(.)
_cons	0.744***	0.744***	0.768***	0.767***
	(0.0573)	(0.0601)	(0.0596)	(0.0593)
N	62	62	62	62
R^2	0.268	0.313	0.316	0.354
adj. R^2	0.188	0.209	0.198	0.212

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: Author, 2022

Table 14. Models 5 - 8 M

	(5M)	(6M)	(7M)	(8M)
Digital Inclusion Index	**Model 5M**	**Model 6M**	**Model 7M**	**Model 8M**
age	-0.00275**	-0.00153	-0.00254*	-0.00133
	(0.00102)	(0.00118)	(0.00104)	(0.00118)
income	0.00228	0.00467	-0.000540	0.00169
	(0.00630)	(0.00581)	(0.00509)	(0.00560)
educ	0.0280	0.0195	0.0349	0.0245
	(0.0224)	(0.0207)	(0.0208)	(0.0201)
soc_incl	0.0304	-0.00305	0.00387	-0.0306
	(0.0704)	(0.0729)	(0.0696)	(0.0693)
nondutch_self	-0.0916*		-0.0956**	
	(0.0452)		(0.0351)	
nondutchparent	0.000879	-0.0208		
	(0.0264)	(0.0259)		
turkey_natl		-0.0945		-0.117
		(0.0813)		(0.0820)
morocco_natl		-0.268***		-0.328***
		(0.0262)		(0.0382)
eucitizen_exdutch		-0.00928		-0.0218
		(0.0243)		(0.0244)
curacao_hert			0.0285	0.0550
			(0.0233)	(0.0300)
morocco_hert			-0.0589	0.0446
			(0.0685)	(0.0344)
suriname_hert			-0.118	-0.0887
			(0.0969)	(0.0928)
turkey_hert			-0.0413	0
			(0.0897)	(.)
pakistan_hert			-0.0374	-0.0392
			(0.0378)	(0.0415)
_cons	0.876***	0.856***	0.900***	0.864***
	(0.0792)	(0.100)	(0.0782)	(0.0976)
N	52	52	52	52
R^2	0.283	0.330	0.367	0.378
adj. R^2	0.188	0.205	0.213	0.206

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: Author, 2022

i. Age:

For women, age is not a robust determinant of digital inclusion; it is only significant at 10% confidence in two of the eight models and with relatively small coefficients, demonstrating marginal difference per increased year of age. For men, however, age is significant at 5% or 10% confidence in five of the eight models. In all the male models in which age is significant, it has a negative effect on digital inclusion. For men, as age increases, it is more strongly expected that their digital inclusion will decrease, holding other factors constant. The coefficients for men are also consistently small, indicating that the magnitude of inclusion change is small for each year of increased age, but over time, the consequence is significant.

ii. Education:

For women, education is a significant determinant in all models, with a 1% confidence level in seven of the eight models. Education is a categorical variable with primary education as the base category; as women's educational attainment increases from one category to the next, it is expected that their digital inclusion will also increase, holding other factors constant. There is a clear connection between higher education and digital inclusion for women in the sample. Contrastingly, for men, education is only significant in one model (2M) and at 10% confidence.

iii. Social Inclusion:

Social inclusion itself is not a significant determinant in any of the stratified models, but by controlling for a person's social inclusion (a composite score created from multiple survey questions), it increases the adj-R^2 values of the models. The models are improved by holding an individual's social inclusion score constant.

iv. Nationality & Heritage:

The variable 'non-Dutch self' has some importance for women; it is significant in two of the five models in which it is included (5F and 7F) at 10% and 5% confidence, respectively. However, for men, it is significant in all models in which it is present. It has a consistently negative coefficient, suggesting that for men, being non-Dutch is associated with a decrease in expected Digital Inclusion score, holding other factors constant. The same is true for women, but with less consistency. When looking at specific non-Dutch ethnicity variables, however, there *is* an effect of having a foreign nationality or heritage for both genders. Based on this sample, the robustness of effect, significant countries of origin, and direction of the effect are varied between men and women.

For women, Turkish nationality is associated with a decrease in expected Digital Inclusion score, holding other factors constant (Models 6F and 8F); Turkish heritage has the same effect (Models 7F and 8F), though with lower confidence. For men, Moroccan nationality is associated with a decrease in expected Digital Inclusion score, holding other factors constant (Models 6M and 8M), significant at 1%. Moroccan nationality also has a negative effect for women in one model, 8F, though this is offset by a significant, positive coefficient for Moroccan heritage. These identity relationships are modeled with additional detail in Section 4.5 to explore more deeply who is digitally excluded.

Interestingly, in Models 5 through 8 F and M, which contain the specific nationality and heritage variables, the explanatory power is similar for men and women, with adjusted R^2 values between 0.18 and 0.21. However, in the models looking at aggregate nationality and heritage variables (Models 1 through 4), the explanatory power is quite varied. Models 2F and 2M are the most explanatory for female and male respondents respectively, but Model 2F has an adjusted R^2 of 0.255, while Model 2M's is 0.1 higher at 0.355. This gives further weight to the idea that while gender itself may not be a determinant of Digital Inclusion score, there are clear differences between the genders in what *does* impact and explain the digital divide for each of them. The included variables are more explanatory for men than they are for women, suggesting unobserved or unmeasurable factors which may better explain women's expected Digital Inclusion scores.

v. Log Transformation:

Finally, considering the literature recommendation to use both compound variables and log-transformations, Models 1 through 8 F and M were also conducted with the log-transformed index as the dependent variable (Vehovar et al., 2006). In these models, the conclusions were similar, with some small differences. Log transformed models are included in Annex 3 through 6 in the Appendix 1.

For women, the non-Dutch nationality variable shows slightly more robust and consistent significance in the log-lin models. Being non-Dutch is associated with a lower Digital Inclusion score for women in three of the five log-lin models, holding other factors constant: one additional model than in the linear form. For men, the log-lin models support the negative effects of age and non-Dutch self that were found in the linear models. The negative effect of

Moroccan nationality is also confirmed. However, the significance of age is weaker and less robust in the log-lin models.

To summarize, while education and age are accepted to be consistent determinants of digital inclusion through previous studies (van Dijk, 2006; van Dijk & Hacker, 2003), when analyzing this sample, they are only reliably significant for women and for men respectively, *not* both. Furthermore, ethnic identity is important in both male-only and female-only models, but in varying levels and with different subgroups contributing to the significance of the aggregated non-Dutch variables. In nearly all cases, however, the coefficient of identity variables which reflect belonging to the minority group(s) are negative, suggesting that a person's Digital Inclusion score is expected to be lower if they are a member of that group.

To further verify these results, a decomposition analysis was conducted per the recommendation of intersectional studies literature (Bauer et al., 2021). Based on the regression findings above, decompositions were performed for gender and ethnic identity variables to further illuminate their differences. However, only the ethnicity models were significant.

Like the multiple regressions above, the OB Decompositions on digital inclusion were ran with the log-transformed index and the as-is index. The findings on significance, sign, and relevant variables were the same in both model versions. Therefore, the following tables and interpretations pertain to the Digital Inclusion index in its original form for ease of interpretation. All models controlled for age, education, income, and employment status. Model 9 controlled for non-Dutch nationality and non-Dutch heritage. Models 10 and 11 controlled for gender.

Table 15. Models 9 -12

	(9)	(10)	(11)	(12)
Digital Inclusion Index	**OB: 'Female'**	**OB: 'non-Dutch Self'**	**OB: 'non-Dutch Parent'**	**OB: 'non-Dutch * Female'**
OVERALL				
Group 1 (reference)	0.838***	0.863***	0.865***	0.845***
	(0.0167)	(0.0107)	(0.0183)	(0.0115)
Group 2 (focal)	0.842***	0.802***	0.833***	0.823***
	(0.0125)	(0.0193)	(0.0118)	(0.0205)
Difference	-0.00418	0.0615**	0.0316	0.0222
	(0.0208)	(0.0220)	(0.0218)	(0.0235)
Explained	-0.00253	-0.0112	0.00242	0.00101
	(0.0130)	(0.0133)	(0.0126)	(0.0162)
Unexplained	-0.00165	0.0727***	0.0292	0.0212
	(0.0173)	(0.0194)	(0.0187)	(0.0207)
Observations	136	136	136	136

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: Author, 2022

The most significant difference, with 5% confidence, is between the Dutch reference group and the non-Dutch focal group in Model 10, with a difference in expected Digital Inclusion scores of 0.0615. In this result, the expected Digital Inclusion index score of a Dutch person, holding age, education, income, gender, and employment status constant, is 0.865 (on a scale of 0 to 1). For a non-Dutch person, the expected index score is 0.802. The *unexplained* portion of this difference is 0.0727 and highly significant (1% confidence). This means that the digital inclusion difference between Dutch and non-Dutch individuals is due to some combination of unobserved variables and a discrimination effect (Jann, 2008). There is an element of the difference attributable to bias.

In more detailed tables found in the Appendix (Annex 7), the explained and unexplained components are broken down further. Within the *unexplained* portion of the residual for Model 10, 'female' is significant at 10% confidence, with a coefficient of -0.0405. This means that being female is significant in reducing the *unexplained* difference between Dutch and non-Dutch individuals. In other words, non-Dutch women and Dutch women are less different than non-Dutch men and Dutch men. Being female also reduces the *unexplained* portion of difference in the non-Dutch Parent Model 11, though the overall unexplained residual is not significant in that model. Women with non-Dutch parents are less different from the reference group than men with non-Dutch parents. These relationships are mirrored in the prior OLS regressions, where different nationalities had different effects for men and women.

In Model 10, the sub-component of age is significant at 10% confidence within the *explained* difference residual, with a coefficient of -0.0151, visible in Annex 7 in the Appendix. This indicates that differences in age observed in the sample significantly explain part of the difference in Digital Inclusion scores for Dutch vs. non-Dutch individuals. This parallels the regression findings that increased age partially explains lower digital inclusion for men, holding other factors constant; though in this case, age is partially explanatory for both genders.

Breaking down the Digital Inclusion index into its sub-indices for OB decomposition analyses confirms the aforementioned findings. In decompositions of Motivational Access, Skills Access, and Usage Access, elements of or the entire difference between groups are consistently significant for the non-Dutch and Dutch models, as before (see: Annex 8 through 10 in Appendix). For Material Access, none of the group decompositions were significant, consistent with the finding that most of the population has achieved this type of access.

For Motivational Access, the *unexplained* difference for Dutch vs. non-Dutch individuals is significant at 5% confidence, with an expected coefficient difference of 0.057, lower for non-Dutch individuals. This means that the motivational score for non-Dutch individuals is lower due to some combination of unobserved variables and a discrimination effect (Jann, 2008).

For Skills Access, the *unexplained* difference for Dutch vs. non-Dutch individuals is significant at 10% confidence, with an expected coefficient difference of 0.035, lower for non-Dutch individuals. This means that the skills index score for non-Dutch individuals is lower due to some combination of unobserved variables and a discrimination effect (Jann, 2008). In the Skill Access decompositions, age is also a significant *explained* difference factor for non-Dutch Self, non-Dutch Parent, and non-Dutch female models (at 5%, 10%, and 1% respectively). This parallels regression findings that age partially explains digital exclusion for men, holding other factors constant; though here, it is partially explanatory for both genders.

For Usage Access, the overall difference for both non-Dutch Self and non-Dutch Parent models is significant at 10%, with expected coefficient differences of 0.0494 and 0.0506 respectively. This means that the usage score for non-Dutch individuals, both by nationality and parental heritage, is lower due to some combination of unobserved variables and a discrimination effect (Jann, 2008). Within the non-Dutch Self model, the *unexplained* difference is also significant, at 5% confidence. This indicates that again, there is a discrimination effect or some element of difference attributable to bias connected to ethnic identities. It is unexplainable by the other included variables. When considering Usage Access alone, the discrimination effect is visible in both the individual nationality and heritage models.

In sum, the OB decomposition models on the digital inclusion index and its sub-components show that ethnic background is a relevant determinant of difference. The *unexplained* difference between the non-Dutch focal group and the Dutch reference group is reliably significant, suggesting a discrimination element. Underneath this, gender has some contribution, particularly the off-setting effect of being female. This is mirrored in the previously-conducted stratified models, where aggregate variables for foreign nationality or heritage were less explanatory for women than for men. The precisely relevant intersections of gender and ethnic identity are further explored in Section 4.5.

Average scores for the target groups confirm the findings on difference between genders and across ethnic identities.

Table 16. Focal Group Averages

Female	Mean
0	0.832
1	0.828
difference	*-0.004*

non-Dutch Parent	Mean
0	0.873
1	0.817
difference	*-0.055*

non-Dutch Self	Mean
0	0.857
1	0.784
difference	*-0.073*

Female non-Dutch	Mean
0	0.837
1	0.803
difference	*-0.034*

Overall Mean:	0.8298

Source: Author, 2022

The expected minority or disadvantaged focal groups have means lower than the sample mean and lower than their contrasting reference groups. The mean scores verify what was observed in the statistical models (OLS and OB) regarding relationships between gender, disadvantage, and digital inclusion.

4.4 Breaking Down Skills, Usage, & Perception by Gender

Q2: In what ways are skills, usage, and perceptions about ability different between women and men?

Within the Digital Inclusion index, Skills Access was more robustly modeled with OLS; the studied variables were more explanatory in predicting an individual's skill index score than digital inclusion in general (see: Annex 1 and 11). Additionally, literature suggests that perception, stereotypes, and gender may influence these usage and skills more directly (Hilbert, 2011; van Deursen et al., 2011). The combination of these considerations encourages deeper exploration of skills, usage, and perception.

i. Skills

The Skills Access index contains five sub-components. To analyze potential difference, the minimum and maximum values, as well as percentiles and mean values were split for women and men.

Table 17. Women Digital Skills

	Women								
	Min	10%	25%	50%	75%	90%	Max	Mean	Obs
Operational Skills	0	0.571	0.857	1	1	1	1	0.887	99
Info Seeking Skills	0	0.350	0.700	0.900	1	1	1	0.796	100
Content/Software Skills	0	0.088	0.500	0.762	0.950	1	1	0.662	100
Safety/Security Skills	0	0.200	0.567	0.733	0.933	1	1	0.697	100
Problem Solving Skills	0	0.200	0.600	0.800	1	1	1	0.709	100

Source: Author, 2022

Table 18. Men Digital Skills

	Men								
	Min	10%	25%	50%	75%	90%	Max	Mean	Obs
Operational Skills	0.286	0.571	1	1	1	1	1	0.919	73
Info Seeking Skills	0	0.400	0.600	0.800	1	1	1	0.771	79
Content/Software Skills	0	0	0.400	0.775	0.950	1	1	0.656	79
Safety/Security Skills	0	0	0.467	0.733	0.867	1	1	0.646	79
Problem Solving Skills	0	0.200	0.600	0.800	1	1	1	0.715	79

Source: Author, 2022

The following table outlines the differences between women and men.

Table 19. Skills by Gender

	Difference							
	Min	10%	25%	50%	75%	90%	Max	Mean
Operational Skills	*-0.286*	0	*-0.143*	0	0	0	0	*-0.032*
Info Seeking Skills	0	*-0.050*	*0.100*	0.100	0	0	0	*0.025*
Content/Software Skills	0	*0.088*	*0.100*	*-0.013*	0	0	0	*0.006*
Safety/Security Skills	0	*0.200*	*0.100*	0	*0.066*	0	0	*0.051*
Problem Solving Skills	0	0	0	0	0	0	0	*-0.006*

Source: Author, 2022

In general, the differences show that women's ranking of their skills is comparable to men's, with marginal differences in positive and negative directions. Literature suggests that women's self-perception is generally lower than men's, even if practically speaking their skills are the same i.e. in a skill-based test vs. this survey format which asked respondents to evaluate themselves (van Deursen et al., 2011). With this insight, lower scores for women were expected due to the self-reporting nature of the collected data. The differences in this sample are small—between 0.006 and 0.143 points—within the index from 0 to 1, but they are present. The signs, however, are unexpectedly varied. In this study, men and women are nearly equal in their self-evaluation of skills, with some minor differences in both positive and negative directions, contrary to the suggestion of previous studies.

ii. Usage

Regarding digital usage, literature also suggests a difference between genders (van Deursen et al., 2015). The percentage of respondents who reported conducting the following activities online in the past twelve months is outlined below.

Table 20. Usage by Gender

	Percentage of Women	Percentage of Men
Email	95%	99%
Music	74%	75%
Gaming	26%	48%
Leisure Searches	77%	66%
Practical Searches	66%	57%
Courses/Trainings	35%	35%
News	73%	73%
Job Search/Application	31%	29%
Shopping	78%	63%
Online Reviews	23%	20%
Social Media	52%	42%
Sharing Photos/Videos	61%	54%
Other	10%	11%

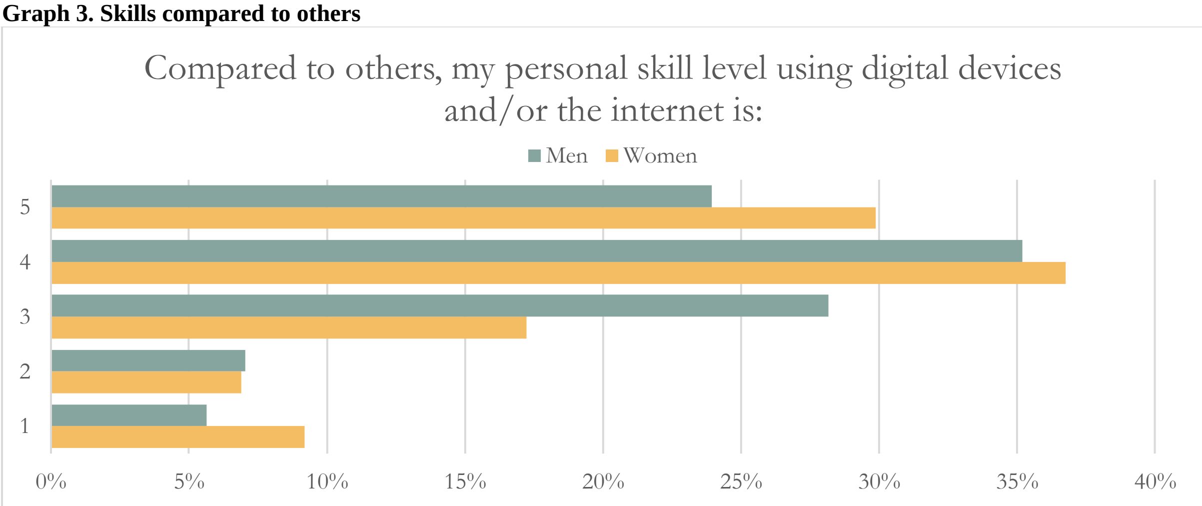
Source: Author, 2022

More men cited gaming as an internet use; more women selected leisure and practical searches, social media, shopping, and sharing photos/videos. These categories demonstrated the most difference between genders. In contrast, email, music, news, job search, online reviews, and courses/trainings are all used in equal or near equal percentages within the sample. Less 'serious' uses (i.e. social media) are typically more associated with being female while men are more associated with 'intellectual' internet uses (van Deursen et al., 2011; van Dijk, 2017). In this sample, both men and women use the internet for higher level activities (news, education/courses, etc.), but women also have higher usages in the expected categories (van Deursen et al., 2011). Ultimately, on the topic of usage, the observed data aligns with literature and evidence from other studies on the digital divide but with women more included in constructive usages more than expected.

iii. Perception

For the final consideration of Q3—self-perceptions and digital inclusion—the following questions were compared between genders.

Graph 3. Skills compared to others

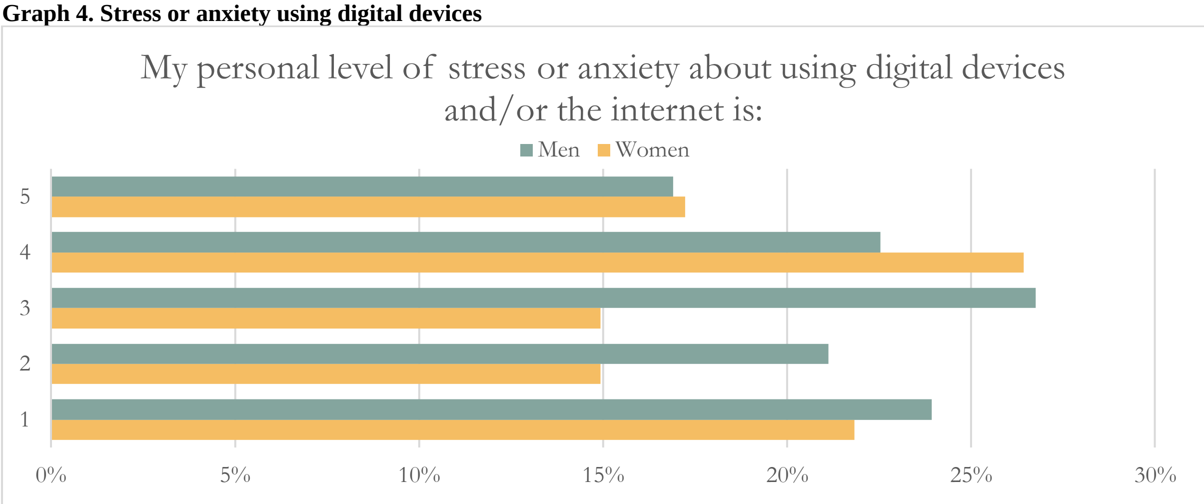


Source: Author, 2022

Respondents were asked to evaluate the above statement on personal skills compared to others with a value of 1 to 5, with 1 meaning lowest skill level and 5 meaning highest. A higher percentage of women ranked themselves as 4 or 5 (high-skilled) than men did. However, a higher percentage of women also ranked themselves as 1 (lowest-skilled). Markedly more men responded with 3 than women, considering themselves in the middle. This question specifically asked respondents to compare themselves to others because literature suggested women would be more conservative in self-evaluation (van Deursen et al., 2011); the question served as an explicit test of self-perception relative to others. In this sample, the literature-suggested difference is seemingly untrue. This finding validates the previous skill investigation above, where women and men were also more equal than literature would suggest.

Another important element connected to usage and motivation is stress as related to the digital realm. Men and women were compared graphically below.

Graph 4. Stress or anxiety using digital devices



Source: Author, 2022

The responses to this question are more evenly distributed between levels (1 being low stress and 5 being high stress) and between genders. Correspondingly, in regression analyses, stress level was not found to be a significant determinant of digital inclusion for women, men, nor the entire sample.

In brief, for this sample population, skills are essentially equally reported between men and women; usages are different as expected, but women are also included in beneficial higher-level uses. Self-perception of skills and reported stress levels are also comparable between genders, validating previous findings on other determinants of difference between men and women.

4.5 Who Exactly is Digitally Excluded?

Q3: From an intersectional perspective, who is digitally excluded in Carnisse, considering gender and ethnicity in particular?

The findings from Q1 models also offered insights in defining who exactly is digitally disadvantaged or likely to be excluded in Carnisse. Based on Q1 results, interaction terms using nationalities and gender were modeled with whole-sample data rather than in split models for men and women.

Table 21. Models 13 - 18

	(13)	(14)	(15)	(16)	(17)	(18)
Digital Inclusion Index	**Turkish Female**	**Moroccan Female**	**non-Dutch Female**	**Turkish Interaction Only**	**Moroccan Interaction Only**	**non-Dutch Interaction Only**
age	-0.00130*	-0.00125*	-0.00204***	-0.00139*	-0.00138*	-0.00154**
	(0.00076)	(0.00075)	(0.00074)	(0.00075)	(0.00075)	(0.00077)
educ	0.0433***	0.0449***	0.0475***	0.0439***	0.0433***	0.0438***
	(0.0105)	(0.0106)	(0.00990)	(0.0105)	(0.0106)	(0.0105)
income	0.00651**	0.00796***	0.00451*	0.00701**	0.00722***	0.00658**
	(0.00281)	(0.00264)	(0.00270)	(0.00273)	(0.00272)	(0.00276)
female	0.00970	0.0111	-0.0274	0.0140	0.0141	0.0209
	(0.0204)	(0.0202)	(0.0213)	(0.0202)	(0.0203)	(0.0211)
turkey_natl	-0.0581					
	(0.0743)					
femaleturkey	-0.0211			-0.0788***		
	(0.0760)			(0.0215)		
morocco_natl		-0.288***				
		(0.0170)				
femalemorocco		0.221***			-0.0673***	
		(0.0279)			(0.0204)	
nondutch_self			-0.122***			
			(0.0322)			
female_intl			0.0867**			-0.0283
			(0.0378)			(0.0228)
_cons	0.720***	0.705***	0.790***	0.715***	0.715***	0.724***
	(0.0554)	(0.0545)	(0.0477)	(0.0545)	(0.0546)	(0.0561)
N	136	136	136	136	136	136
R^2	0.248	0.283	0.345	0.242	0.240	0.243
adj. R^2	0.213	0.250	0.315	0.213	0.211	0.214

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: Author, 2022

In Models 13 through 18, age, education, and income were significant in each model with the expected signs. Holding other factors constant, more educated individuals are expected to have higher Digital Inclusion scores; the same is true for those with higher income categories. Consistently, the lower educated are more likely to experience exclusion. Age has a negative effect; holding other factors constant, older people are expected to have lower Digital Inclusion scores i.e., experience exclusion. The coefficients for age and income, however, are quite small, meaning the change in expected Digital Inclusion score per increment (either additional year of age or change in income category) has a minimal effect. Female is not significant in any models, but the gender interactions indicate significance of gender. These findings match the relationships modeled throughout this research.

To address the intersectional identity focus, the following relationships are most notable:

i. Turkish * Female

When 'female', Turkish nationality, and their interaction term are included in Model 13, none of the variables are significant. However, Models 6F through 8F in Section 4.3 illustrated a strong negative effect of Turkish nationality and heritage on female digital inclusion. Therefore, the model was also tested with *only* the interaction of female and Turkish nationality (see: Model 16). In this instance, the coefficient is negative and highly significant at 1% confidence. Holding other factors constant, Turkish women are expected to have Digital Inclusion scores that are 0.0788 points lower than others, i.e., Turkish women are more likely to be digitally excluded. Both Turkish-focused models have an adjusted R^2 of 0.213, consistent with other explanatory percentages observed throughout this research.

ii. Moroccan * Female

Model 14 shows that Moroccan nationality and its interaction with ‘female’ are highly significant (1% confidence) in explaining Digital Inclusion scores in this sample. Their inverse signs show a difference in effect for men and women. The nationality variable alone indicates that holding other factors constant, an individual with Moroccan nationality is expected to have a Digital Inclusion score 0.288 points lower than others, indicating exclusion relative to the rest. Conversely, the interaction term of female and Moroccan nationality has a large and positive coefficient of 0.221; the negative effect of Moroccan nationality is offset by being female. In other words, Moroccan men are expected to have lower Digital Inclusion scores than Moroccan women, though *both* are disadvantaged relative to the rest of the sampled population. This is confirmed in Model 17, where the Moroccan female interaction term has a coefficient of -0.0673, significant at 1%.

iii. non-Dutch * Female

Finally, the aggregate non-Dutch nationality variable and ‘female’ were studied in Models 15 and 18. Model 15 shows that holding other factors constant, a non-Dutch individual is expected to have a Digital Inclusion score 0.122 points lower than others, significant at 1%. When interacted with female, the coefficient is 0.0867, significant at 5% confidence. Again, this illustrates the difference of nationality’s effect across genders. In this model, non-Dutch men are more disadvantaged than non-Dutch women. The adjusted R^2 of this model is highest at 0.315; this is likely explainable by the number of observations for each individual nationality. As reviewed in Section 4.1 Data Description, 23 unique nationalities were listed by respondents. These foreign nationalities are considered jointly in this model, whereas the prior models consider the relatively small number of Turkish and Moroccan respondents in detail.

Ultimately, as was also found in the regression analyses conducted for Q1, ethnic background is demonstrably nuanced between men and women. Turkish women, Moroccan men, and foreign individuals in general are notably more likely to be excluded. However, it is important to note that while these findings are indicative of which ethnicity and gender intersections are significant in the sample, a larger dataset is needed to truly conclude relevance and go deeper than analyzing the foreign population in a combined sense.

5. Discussion

The results of this research both confirm and contrast the established pillars of theory on the digital divide. The study and methodologies also contribute novelty to existing literature. Reflecting on Chapter 4, the obtained results are debated in light of existing studies.

Firstly, the analysis confirmed historical findings in that on its own, gender is not a relevant determinant for digital inclusion or exclusion in the sample population. However, stratified sample regressions were also conducted, which demonstrated significant differences in determinants when men and women were analyzed independently. Education was found to be highly significant for women; as education increases, so does the expected female Digital Inclusion score. This finding aligns with historical analyses of gender (see: Cooper, 2006) which suggested that the environments in which technology skills are typically learned and performed i.e. education, are more tailored to males. Consequently, it is unsurprising that higher levels of education benefit female digital inclusion in a way that is not reproduced in the studied male population; the higher returns of education for women fit previously-confirmed patterns. A similar effect of education for women has also been demonstrated qualitatively (see: Arroyo, 2020). For men, age was robustly significant; as age increases, the expected male Digital Inclusion score decreases. The negative relationship between inclusion and older populations is demonstrable throughout digital divide research, though the applicability to only men is a new finding of this study (see: van Dijk, 2006; van Dijk & Hacker, 2003).

Furthermore, Moroccan nationality for men and Turkish nationality for women were most associated with lower Digital Inclusion index coefficients in the gender-stratified models, holding other factors constant. These findings were further confirmed in whole-sample regressions which considered interaction terms for gender and nationality. Literature on Rotterdam's superdiversity verifies that individuals of Turkish and Moroccan descent are most disadvantaged in the city, generally speaking (Scholten et al., 2019). This is seen in the digital divide data as well. Additionally, there is evidence that "the diversity *within* the group of Turkish and Moroccan descent is increasing over generations", something the varied results between models potentially display (Scholten et al., 2019).

For both men and women, aggregate foreign nationality was demonstrably negative in its effect on digital inclusion. This was expected based on prior study's findings on the lower inclusion levels for minority groups (Hilbert, 2011). However, in Rotterdam, as a majority-minority city, the interpretation of this finding is less straightforward. While they are not a minority in number, the foreign population in Carnisse still experiences disadvantage in the digital realm. Through the OB decompositions, it was further confirmed that a non-Dutch person compared to a Dutch person will likely have a lower digital inclusion score with a significant *unexplained* component–attributable to some combination of discriminative bias and unobserved variables. Concerns for digital access for foreign language speakers and other disadvantaged groups found in qualitative studies mirror the quantitative results (see: Goedhart et al., 2019).

It is clear that there is a negative relationship between being digitally included and having a foreign nationality or heritage, but with the small sample size, robust conclusions are difficult to achieve. Gender is also associated with differences in relevant factors for digital inclusion, but in connection with other variables (education, age, ethnic identity) rather than on its own. Compared to prior studies, the stratified and decomposed modeling conducted in this research addresses the gap of application of gender study perspectives to the digital divide. Typical digital inclusion research considers gender as a factor or control variable but does not go deeper. This research indicates that this is an oversight that should be addressed in future studies.

The digital divide concept was constructed in this study as a composite of four types of access—Motivational, Material, Skills, and Usage. The final two components were studied individually based on prior research. Regarding skills, on a country level, Dutch women were found to be lower skilled than men in categories comparable to the ones used in this study (Kang & Junio, 2019). In this neighborhood sample, however, men and women in Carnisse scored themselves nearly equally in the skill sub-categories. Contrary to literature suggestion (see also: van Deursen et al., 2011), the gender differences were negligible and both positive and negative in sign. Importantly, this unexpected finding enhances the validity of the study of gender, as one limitation of self-reported surveys is the potential to over- or underestimate oneself. While that limitation remains for the dataset as a whole, there is no demonstrable difference between the self-evaluation of men and women, adding robustness to the other findings of difference between genders.

Regarding usage, in this sample, both men and women use the internet for higher level activities, but women also have higher usages in the expected socially-focused categories (van Deursen et al., 2011). This is promising for the state of the third-level divide which purports that social and information inequality can still persist due to variation in digital skills and opportunities for usage (Scheerder et al., 2017); while women in the sample are heavier users of less 'intellectually-beneficial' online activities like social media and shopping, they are seemingly not left out of the benefits of online connectivity. The collected data supports evidence from other studies on gender and the digital usage, with slightly more parity than expected. Overall, the findings of this research confirm and add to existing literature on the digital divide while also offering contrasts which may encourage future inquiry.

6. Conclusions

Through this research, quantitative intersectional analysis of primary data collected in Carnisse was conducted to explore which demographic factors, with particular attention to gender, are associated with being digitally divided. In depth consideration was given to the topics of skills, usage, multiplicity of identity, and self-perception per findings of this research, prior studies, and the selected gender-analysis lens. Two important overarching contributions were the addition of detailed gender studies to the digital divide debate in general, and the specific use of Oaxaca-Blinder Decompositions to add intersectionality considerations.
In response to the research question and sub-questions, the following conclusions and recommendations were determined.

6.1 Conclusions on Q1

Q1: What are the determinants of digital exclusion for women compared to men in Rotterdam?

Men and women were demonstrably different in what determines or explains their level of digital inclusion, even though gender *itself* is not a determinant or explanatory factor of the digital divide. While gender may not explain the digital divide in Carnisse, separating the population by gender gives deeper insight into who is excluded, and which factors contribute to that exclusion. For women, increasing levels of education clearly result in increased digital inclusion. This determinant in particular was only significant for women, something previously unexplored in the digital divide despite connections to existing studies on gender. For men, there is a concern for age; older men have lower levels of digital inclusion. For both genders, foreign nationality is also associated with lower digital inclusion, but with differing strengths and countries of relevance. Ultimately, it is not so simple as explaining the digital divide with personal characteristics; stratifying based on gender reveals differing sources of disadvantage for men and women.

6.2 Conclusions on Q2

Q2: In what ways are skills, usage, and perceptions about ability different between women and men?

Results reveal that for the surveyed population, skills are relatively equally reported between genders. With small divergences in each direction, men and women are only marginally different in their operational, information seeking, software and content creation, safety and security, and problem-solving skills. However, as noted in Q1, the causes for the variation that does exist within the sample *are* different for men and women. Particular focus is seemingly not required for any subset of skills related to gender, rather, other differences should be emphasized when addressing the digital divide in Carnisse.

Usages are different between men and women as expected, but both genders seem to benefit from higher-level uses like education and news. Typically, a usage gap manifests in the aforementioned areas. In this sample, more women than men reported socially-focused usages, but at the same time, they were not lagging behind men in the higher-level uses. Though usage was observably different between genders, it did not manifest in an explicitly disadvantaged way.

Finally, the role of self-perception is limited in its potential explanatory power for gender differences. Men and women have comparable levels of personal skill perception relative to others and report similar levels of stress. Consequently, the other considered factors explaining digital difference between genders are reinforced in their significance. Because the self-perception bias is minimal, it enhances the observations distinguishing women from men mentioned throughout this research.

6.3 Conclusions on Q3

Q3: From an intersectional perspective, who is digitally excluded in Carnisse, considering gender and ethnicity in particular?

In the Q1 models, analysis revealed unexplainable difference between Dutch and non-Dutch individuals in the sample; other models demonstrated the significance of various ethnic identities for women and men respectively. Those conclusions led to further investigation of Turkish, Moroccan, and the aggregate non-Dutch population.

When targeting who exactly is digitally excluded, a few profiles emerge. Turkish women are expected to have lower digital inclusion levels, holding other factors constant. It was also found that Moroccan men are expected to have lower Digital Inclusion scores than Moroccan women, though both are disadvantaged relative to the rest of the sampled population. For the general non-Dutch population, when modeling the entire dataset, non-Dutch men are shown to be more disadvantaged than non-Dutch women, though specific categories of non-Dutch women (i.e., Turkish) are demonstrably disadvantaged too. Considering the foreign nationalities together led to the conclusion that there is a detrimental effect on digital inclusion if you do not have Dutch nationality, for both men and women.

Ultimately, the connection between ethnic background and digital inclusion is discernibly not straightforward—which exact ethnic identities cause disadvantage, and how that is layered with gendered-discrimination is suggested but not exceedingly clear in this research, largely due to insufficient observations of the sub-groups. Turkish women and Moroccan men stand out as potential groups experiencing digital exclusion in Carnisse, but without more data, this cannot be confirmed with certainty. While these findings are indicative of the roles of ethnicity and heritage in the digital divide, a larger dataset is needed to conclude their exact relevance and analyze foreign populations separately and specifically.

6.4 Recommendations for Policy

Based on the differences observed between men, women, foreign, and Dutch respondents, targeted policies for each digitally excluded group are recommended. Consistently, foreign nationality respondents demonstrated lower digital inclusion levels per the measures of this research. Digital inclusion policies in Carnisse, therefore, should account for the superdiversity of the sample population, via tangible actions like multi-language offerings of digital skill improvement classes or specific promotion of planned intervention offerings to the non-Dutch population. Concerning the study of gender, older men and lower educated women are groups vulnerable to digital exclusion and require fitted policies to suit their needs and deficits. While older and lower educated people in general are less digitally included, gender-sensitive policy is clearly needed based on these results.

6.5 Recommendations for Future Research

Regarding methodology, using the Oaxaca-Blinder Decomposition to study the digital divide had not been done before; in this case, it added legitimacy to the findings on group difference, digital inclusion or exclusion, and how well they are explained by demographics. Usage of this method in future studies, particularly with larger sample sizes, is recommended. A multilevel modeling approach using non-nested groups (gender and ethnicity) would also offer deeper insights to gender, ethnic identity, their intersections, and the digital divide. Related to data processing, there is an ongoing research debate of how to weigh variables when creating an index – for purpose of this study, they were weighed equally. The DESI index of digital skills weighs the sub-sections equally and was used as a model for the index creation method, principally for ease of interpretation. Within literature, it is inconclusive about what method is 'best' for creating an index.

Further refinement of the data collection instrument is also advisable. The length and nature of the survey used in this research, often taking around 10-15 minutes to complete and including complicated topics, meant fewer people were willing to participate. While it delivered strong results because of its comprehensiveness, still certain questions within the survey needed refinement. For example, respondents were asked about the types of and number of owned digital devices, but unclear composition led to incomplete and unusable responses. In the future, having more quantifiable information on these topics would be useful.

Ultimately, the strongest recommendation of this research is for more data collection in Carnisse and other Rotterdam neighborhoods to better study identity subgroups– a much larger sample is needed to robustly analyze specific nationalities and heritages and their interactions with gender. Conclusions from this study confirm the relevance of gender and superdiversity to digital inclusion but require more research. Many nationalities, heritages, and native languages were present in this study, but not in large enough sub-populations for truly concrete and tailored policy suggestions.

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Appendix 1: Additional Tables

Annex 1. Does gender matter?

Digital Inclusion Index	**Simple Model**	**Simple + non-Dutch**	**Simple + Interaction**	**Simple + non-Dutch (Specific)**	**Simple + non-Dutch Parent**	**Simple + non-Dutch Parent (Specific)**
female	0.0122	0.00453	-0.0274	0.00615	0.0113	0.0150
	(0.0200)	(0.0183)	(0.0213)	(0.0189)	(0.0197)	(0.0220)
age	-0.00139	-0.00206**	-0.00204**	-0.00186*	-0.00156*	-0.00134
	(0.000749)	(0.000759)	(0.000744)	(0.000785)	(0.000758)	(0.000780)
educ	0.0439***	0.0458***	0.0475***	0.0446***	0.0440***	0.0437***
	(0.0104)	(0.0102)	(0.00990)	(0.0103)	(0.0104)	(0.0106)
income	0.00712**	0.00457	0.00451	0.00512	0.00621*	0.00705*
	(0.00272)	(0.00274)	(0.00270)	(0.00276)	(0.00278)	(0.00282)
nondutch_self		-0.0727***	-0.122***			
		(0.0203)	(0.0322)			
female_intl			0.0867*			
			(0.0378)			
turkey_natl				-0.0265		
				(0.0533)		
morocco_natl				-0.0949		
				(0.0625)		
poland_natl				-0.00365		
				(0.0546)		
dutch_natl				0.0609**		
				(0.0221)		
nondutchparent					-0.0281	
					(0.0195)	
curacao_hert						-0.00212
						(0.0468)
morocco_hert						-0.0353
						(0.0465)
suriname_hert						-0.0380
						(0.0389)
pakistan_hert						0.00345
						(0.0395)
turkey_hert						-0.0458
						(0.0320)
Constant	0.714***	0.778***	0.790***	0.708***	0.747***	0.720***
	(0.0542)	(0.0509)	(0.0477)	(0.0510)	(0.0547)	(0.0584)
N	*136*	*136*	*136*	*136*	*136*	*136*
R^2	0.236	0.314	0.345	0.328	0.245	0.255
Adjusted R^2	0.212	0.288	0.315	0.285	0.216	0.202

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: Author, 2022

Annex 2. Does gender matters? Sub-Indices

Independent variables:	Digital Inclusion Index	Material Access	Motivation Access	Skills Access	Usage Access
female	-0.0275	-0.0246	-0.0313	-0.0253	-0.0360
	(0.0216)	(0.0294)	(0.0400)	(0.0393)	(0.0290)
age	-0.00203**	-0.00200	-0.00312*	-0.00523***	-0.00172
	(0.000733)	(0.00162)	(0.00137)	(0.00107)	(0.00111)
educ	0.0475***	0.0435***	0.0371*	0.0706***	0.0584***
	(0.00995)	(0.0119)	(0.0159)	(0.0154)	(0.0115)
income	0.00459	0.0119***	-0.00170	0.0100*	0.00499
	(0.00274)	(0.00353)	(0.00510)	(0.00446)	(0.00357)
nondutch_self	-0.123***	-0.0861*	-0.146*	-0.138**	-0.111**
	(0.0341)	(0.0424)	(0.0608)	(0.0507)	(0.0348)
female_intl	0.0871*	0.0572	0.102	0.0720	0.104*
	(0.0381)	(0.0605)	(0.0688)	(0.0575)	(0.0427)
nondutchparent	0.00363	0.00430	0.0149	0.0620	-0.0240
	(0.0196)	(0.0305)	(0.0377)	(0.0359)	(0.0278)
Constant	0.787***	0.813***	0.879***	0.730***	0.703***
	(0.0468)	(0.0733)	(0.0795)	(0.0929)	(0.0757)
N	*136*	*151*	*144*	*153*	*150*
R^2	0.345	0.183	0.140	0.374	0.272
Adjusted R^2	0.309	0.143	0.095	0.344	0.236

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: Author, 2022

Annex 3. Ln 1 - 4 F

Ln (Digital Inclusion Index)	Ln(1F)	Ln(2F)	Ln(3F)	Ln(4F)
age	-0.00234	-0.00269	-0.00309	-0.00290
	(0.00155)	(0.00160)	(0.00177)	(0.00165)
income	0.00999*	0.00883*	0.00610	0.00661
	(0.00412)	(0.00421)	(0.00443)	(0.00480)
educ	0.0646***	0.0644***	0.0544***	0.0540***
	(0.0165)	(0.0169)	(0.0154)	(0.0152)
nondutch_self		-0.0368	-0.0645	-0.0712*
		(0.0318)	(0.0323)	(0.0349)
soc_incl			0.0641	0.0608
			(0.0690)	(0.0690)
nondutchparent				0.0304
				(0.0413)
_cons	-0.340***	-0.308***	-0.275***	-0.303***
	(0.0712)	(0.0821)	(0.0680)	(0.0761)
N	77	77	62	62
R^2	0.282	0.295	0.274	0.281
adj. R^2	0.253	0.255	0.209	0.202

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: Author, 2022

Annex 4. Ln 5 - 8 F

Ln (Digital Inclusion Index)	**Ln(5F)**	**Ln(6F)**	**Ln(7F)**	**Ln(8F)**
age	-0.00290	-0.00242	-0.00332	-0.00277
	(0.00165)	(0.00158)	(0.00183)	(0.00178)
income	0.00661	0.00689	0.00519	0.00567
	(0.00480)	(0.00511)	(0.00465)	(0.00478)
educ	0.0540***	0.0417**	0.0560**	0.0425*
	(0.0152)	(0.0150)	(0.0165)	(0.0171)
soc_incl	0.0608	0.0904	0.0954	0.121
	(0.0690)	(0.0673)	(0.0791)	(0.0739)
nondutch_self	-0.0712*		-0.0784*	
	(0.0349)		(0.0351)	
nondutchparent	0.0304	0.0279		
	(0.0413)	(0.0400)		
turkey_natl		-0.137***		-0.0993*
		(0.0355)		(0.0420)
morocco_natl		-0.0492		-0.0866***
		(0.0323)		(0.0191)
eucitizen_exdutch		-0.118		-0.132
		(0.0630)		(0.0664)
curacao_hert			-0.104	-0.0989
			(0.0673)	(0.0682)
morocco_hert			0.0310	0.0444
			(0.0223)	(0.0226)
suriname_hert			-0.0238	-0.0179
			(0.0525)	(0.0486)
turkey_hert			-0.0511	-0.0493
			(0.0355)	(0.0310)
pakistan_hert			0	0
			(.)	(.)
_cons	-0.303***	-0.302***	-0.270***	-0.272***
	(0.0761)	(0.0801)	(0.0758)	(0.0762)
N	62	62	62	62
R^2	0.281	0.318	0.314	0.347
adj. R^2	0.202	0.215	0.195	0.204

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: Author, 2022

Annex 5. Ln 1 - 4 M

Ln (DD Index)	**Ln(1M)**	**Ln(2M)**	**Ln (3M)**	**Ln(4M)**
age	-0.00144	-0.00282*	-0.00343*	-0.00343*
	(0.00154)	(0.00133)	(0.00131)	(0.00133)
income	0.0107	0.00251	0.00290	0.00291
	(0.00695)	(0.00762)	(0.00819)	(0.00815)
educ	0.0580	0.0725*	0.0380	0.0380
	(0.0345)	(0.0326)	(0.0303)	(0.0305)
nondutch_self		-0.179**	-0.122*	-0.122
		(0.0543)	(0.0549)	(0.0620)
soc_incl			0.0468	0.0470
			(0.0869)	(0.0888)
nondutchparent				0.000555
				(0.0330)
_cons	-0.378*	-0.253*	-0.152	-0.153
	(0.160)	(0.113)	(0.0995)	(0.102)
N	59	59	52	52
R^2	0.202	0.400	0.287	0.287
adj. R^2	0.159	0.355	0.209	0.191

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: Author, 2022

Annex 6. Ln 5 - 8 M

Ln (Digital Inclusion Index)	**Ln(5M)**	**Ln(6M)**	**Ln(7M)**	**Ln(8M)**
age	-0.00343*	-0.00175	-0.00310*	-0.00150
	(0.00133)	(0.00148)	(0.00130)	(0.00149)
income	0.00291	0.00588	-0.000421	0.00243
	(0.00815)	(0.00738)	(0.00641)	(0.00706)
educ	0.0380	0.0267	0.0463	0.0328
	(0.0305)	(0.0272)	(0.0275)	(0.0264)
soc_incl	0.0470	0.00238	0.0154	-0.0296
	(0.0888)	(0.0912)	(0.0870)	(0.0865)
nondutch_self	-0.122		-0.124**	
	(0.0620)		(0.0447)	
nondutchparent	0.000555	-0.0280		
	(0.0330)	(0.0316)		
turkey_natl		-0.134		-0.162
		(0.114)		(0.115)
morocco_natl		-0.360***		-0.429***
		(0.0320)		(0.0431)
eucitizen_exdutch		-0.00721		-0.0237
		(0.0282)		(0.0279)
curacao_hert			0.0401	0.0748
			(0.0293)	(0.0384)
morocco_hert			-0.0874	0.0486
			(0.0889)	(0.0373)
suriname_hert			-0.153	-0.115
			(0.128)	(0.123)
turkey_hert			-0.0632	0
			(0.120)	(.)
pakistan_hert			-0.0440	-0.0459
			(0.0469)	(0.0516)
_cons	-0.153	-0.180	-0.126	-0.174
	(0.102)	(0.128)	(0.100)	(0.126)
N	*52*	*52*	*52*	*52*
R^2	0.287	0.343	0.376	0.387
adj. R^2	0.191	0.221	0.223	0.218

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: Author, 2022

Annex 7. Models 9 - 12

	(9)	(10)	(11)	(12)
Detailed Decompositions	**OB: Female**	**OB: non-Dutch Self**	**OB: non-Dutch Parent**	**OB: non-Dutch Female**
OVERALL				
Group 1 (reference)	0.838***	0.863***	0.865***	0.845***
	(0.0167)	(0.0107)	(0.0183)	(0.0115)
Group 2 (focal)	0.842***	0.802***	0.833***	0.823***
	(0.0125)	(0.0193)	(0.0118)	(0.0205)
Difference	-0.00418	0.0615**	0.0316	0.0222
	(0.0208)	(0.0220)	(0.0218)	(0.0235)
Explained	-0.00253	-0.0112	0.00242	0.00101
	(0.0130)	(0.0133)	(0.0126)	(0.0162)
Unexplained	-0.00165	0.0727***	0.0292	0.0212
	(0.0173)	(0.0194)	(0.0187)	(0.0207)
EXPLAINED				
age	-0.00937	-0.0151*	-0.0106	-0.0134
	(0.00572)	(0.00699)	(0.00690)	(0.00704)
educ	0.00300	-0.00278	0.00269	0.00438
	(0.00780)	(0.00874)	(0.00792)	(0.0111)
income	0.00925	0.00851	0.0145	0.0158*
	(0.00547)	(0.00527)	(0.00746)	(0.00773)
employed	-0.00476	-0.00180	-0.00358	-0.00579
	(0.00378)	(0.00271)	(0.00363)	(0.00476)
nondutchparent	0.0000287			
	(0.000909)			
nondutch_self	-0.000670			
	(0.00610)			
female		0.0000161	-0.000537	
		(0.000224)	(0.00148)	
UNEXPLAINED				
age	-0.0162	0.0320	-0.135*	0.0586
	(0.0511)	(0.0574)	(0.0572)	(0.0928)
educ	-0.0103	-0.0471	-0.0395	0.0292
	(0.0663)	(0.0577)	(0.0624)	(0.0537)
income	-0.00552	-0.0339	0.0283	-0.00159
	(0.0369)	(0.0260)	(0.0346)	(0.0191)
employed	-0.0452*	0.0538**	-0.00874	0.00539
	(0.0222)	(0.0205)	(0.0237)	(0.0216)
nondutchparent	-0.0223			
	(0.0296)			
nondutch_self	-0.0296			
	(0.0173)			
female		-0.0405*	-0.0363*	
		(0.0193)	(0.0181)	
Constant	0.127	0.108	0.221**	-0.0704
	(0.0891)	(0.0946)	(0.0836)	(0.110)
Observations	*136*	*136*	*136*	*136*

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: Author, 2022

Annex 8. Models OB Motivation

MOTIVATION ACCESS	**OB: Female**	**OB: non-Dutch Self**	**OB: non-Dutch Parent**	**OB: non-Dutch Female**
OVERALL				
Group 1 (reference)	0.809***	0.844***	0.824***	0.822***
	(0.0276)	(0.0193)	(0.0370)	(0.0192)
Group 2 (focal)	0.834***	0.787***	0.823***	0.828***
	(0.0194)	(0.0287)	(0.0182)	(0.0282)
Difference	-0.0244	0.0574	0.00172	-0.00585
	(0.0337)	(0.0346)	(0.0412)	(0.0341)
Explained	-0.0222	-0.0295	-0.0231	-0.0287
	(0.0151)	(0.0171)	(0.0185)	(0.0202)
Unexplained	-0.00217	0.0869**	0.0249	0.0229
	(0.0336)	(0.0317)	(0.0350)	(0.0355)
EXPLAINED				
age	-0.0129	-0.0261*	-0.0247	-0.0269
	(0.00949)	(0.0131)	(0.0154)	(0.0144)
educ	0.000216	-0.00153	0.00141	0.00116
	(0.00590)	(0.00654)	(0.00617)	(0.00834)
income	0.00116	0.000708	0.00473	0.00510
	(0.00817)	(0.00689)	(0.00899)	(0.0106)
employed	-0.00802	-0.00267	-0.00447	-0.00807
	(0.00643)	(0.00472)	(0.00575)	(0.00744)
nondutchparent	-0.000105			
	(0.000866)			
nondutch_self	-0.00254			
	(0.00746)			
female		0.0000530	-0.000136	
		(0.00102)	(0.00114)	
UNEXPLAINED				
age	0.0525	-0.0603	-0.343***	0.0682
	(0.103)	(0.101)	(0.0852)	(0.135)
educ	0.0497	0.0388	0.0344	0.173*
	(0.101)	(0.0906)	(0.107)	(0.0853)
income	0.0398	-0.101	-0.0368	0.0178
	(0.0621)	(0.0535)	(0.0657)	(0.0394)
employed	-0.0538	0.0820*	0.000332	0.0321
	(0.0396)	(0.0378)	(0.0462)	(0.0347)
nondutchparent	-0.0406			
	(0.0579)			
nondutch_self	-0.0244			
	(0.0277)			
female		-0.0645	-0.0614	
		(0.0395)	(0.0385)	
Constant	-0.0253	0.192	0.432**	-0.268
	(0.157)	(0.162)	(0.156)	(0.160)
Observations	*144*	*144*	*144*	*144*

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.00$

Source: Author, 2022

Annex 9. Models OB Skills

SKILL ACCESS	**OB: Female**	**OB: non-Dutch Self**	**OB: non-Dutch Parent**	**OB: non-Dutch Female**
OVERALL				
Group 1 (reference)	0.788***	0.799***	0.757***	0.788***
	(0.0264)	(0.0216)	(0.0354)	(0.0198)
Group 2 (focal)	0.785***	0.764***	0.797***	0.782***
	(0.0223)	(0.0275)	(0.0193)	(0.0315)
Difference	0.00282	0.0352	-0.0394	0.00648
	(0.0346)	(0.0349)	(0.0404)	(0.0372)
Explained	0.000475	-0.0426	-0.0178	-0.0279
	(0.0220)	(0.0236)	(0.0271)	(0.0263)
Unexplained	0.00234	0.0778*	-0.0216	0.0343
	(0.0283)	(0.0312)	(0.0337)	(0.0330)
EXPLAINED				
age	-0.0148	-0.0492**	-0.0405*	-0.0504***
	(0.0130)	(0.0154)	(0.0177)	(0.0145)
educ	0.00468	-0.00510	0.00171	0.00591
	(0.0113)	(0.0125)	(0.0121)	(0.0158)
income	0.0155	0.0132	0.0236*	0.0209
	(0.00871)	(0.00832)	(0.0118)	(0.0112)
employed	-0.00395	-0.00142	-0.00253	-0.00425
	(0.00515)	(0.00263)	(0.00385)	(0.00547)
nondutchparent	-0.000281			
	(0.00429)			
nondutch_self	-0.000711			
	(0.00767)			
female		-0.0000396	-0.0000177	
		(0.000482)	(0.000324)	
UNEXPLAINED				
age	0.0513	0.0672	0.0144	0.0181
	(0.0825)	(0.0919)	(0.0831)	(0.134)
educ	-0.0865	0.0399	0.0530	0.0515
	(0.0971)	(0.0911)	(0.0760)	(0.0917)
income	0.0315	-0.00649	0.0659	0.0109
	(0.0562)	(0.0493)	(0.0579)	(0.0467)
employed	-0.0919**	0.0323	-0.0103	-0.00813
	(0.0355)	(0.0340)	(0.0400)	(0.0372)
nondutchparent	-0.00133			
	(0.0534)			
nondutch_self	-0.0192			
	(0.0259)			
female		-0.0278	-0.0122	
		(0.0313)	(0.0347)	
Constant	0.119	-0.0273	-0.132	-0.0380
	(0.167)	(0.168)	(0.156)	(0.192)
Observations	*153*	*153*	*153*	*153*

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: Author, 2022

Annex 10. Models OB Usage

USAGE ACCESS	**OB: Female**	**OB: Non-Dutch Self**	**OB: Non-Dutch Parent**	**OB: Non-Dutch Female**
OVERALL				
Group 1 (reference)	0.785***	0.800***	0.820***	0.785***
	(0.0170)	(0.0156)	(0.0202)	(0.0142)
Group 2 (focal)	0.780***	0.750***	0.769***	0.772***
	(0.0175)	(0.0192)	(0.0148)	(0.0229)
Difference	0.00434	0.0494*	0.0506*	0.0132
	(0.0244)	(0.0248)	(0.0251)	(0.0270)
Explained	-0.000753	-0.0122	0.00210	0.00597
	(0.0146)	(0.0170)	(0.0161)	(0.0202)
Unexplained	0.00509	0.0616**	0.0485	0.00719
	(0.0208)	(0.0238)	(0.0257)	(0.0242)
EXPLAINED				
age	-0.00516	-0.0155	-0.0107	-0.0105
	(0.00522)	(0.0101)	(0.00912)	(0.00951)
educ	0.00266	-0.00517	0.00326	0.00448
	(0.00897)	(0.0102)	(0.00946)	(0.0134)
income	0.0110	0.0104	0.0153	0.0202*
	(0.00666)	(0.00646)	(0.00806)	(0.00959)
employed	-0.00853	-0.00189	-0.00574	-0.00824
	(0.00532)	(0.00391)	(0.00496)	(0.00620)
nondutchparent	0.000215			
	(0.00206)			
nondutch_self	-0.000963			
	(0.00418)			
female		-0.0000775	0.0000139	
		(0.000523)	(0.000248)	
UNEXPLAINED				
age	-0.0273	0.0534	-0.0193	0.00587
	(0.0760)	(0.0739)	(0.0776)	(0.0881)
educ	-0.0254	-0.00829	-0.0742	0.00635
	(0.0652)	(0.0686)	(0.0592)	(0.0645)
income	-0.0755	0.0493	0.0761	0.0112
	(0.0394)	(0.0359)	(0.0429)	(0.0293)
employed	-0.0275	0.0245	-0.0520	0.0104
	(0.0253)	(0.0231)	(0.0285)	(0.0229)
nondutchparent	-0.0173			
	(0.0415)			
nondutch_self	-0.0411*			
	(0.0192)			
female		-0.0378	-0.0296	
		(0.0222)	(0.0237)	
Constant	0.219	-0.0196	0.147	-0.0267
	(0.126)	(0.127)	(0.101)	(0.139)
Observations	*150*	*150*	*150*	*150*

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: Author, 2022

Annex 11. Digital Inclusion Index

Digital Inclusion Index	**Skills Access Model 1**	**Skills Access Model 2**	**Usage Access Model 1**	**Usage Access Model 2**
female	-0.0130	-0.0255	-0.00537	-0.00262
	(0.0304)	(0.0340)	(0.0245)	(0.0244)
age	-0.00629***	-0.00538***	-0.00232*	-0.00134
	(0.00111)	(0.00107)	(0.00116)	(0.00105)
educ	0.0456**	0.0361	0.0436***	0.0329**
	(0.0161)	(0.0205)	(0.0105)	(0.0113)
income	0.00967*	0.00727	0.00580	0.00503
	(0.00471)	(0.00540)	(0.00407)	(0.00420)
nondutch_self	-0.0743*	-0.0736	-0.0616*	-0.0628*
	(0.0349)	(0.0397)	(0.0275)	(0.0304)
nondutchparent	0.0496	0.0742*	-0.0231	0.00148
	(0.0325)	(0.0370)	(0.0276)	(0.0307)
soc_incl	0.0642	0.0396	0.0412	0.0355
	(0.0628)	(0.0713)	(0.0637)	(0.0621)
kids		0.0107		0.00835
		(0.0137)		(0.0120)
fluency in English		0.0514*		0.0590***
		(0.0202)		(0.0160)
Constant	0.821***	0.667***	0.734***	0.532***
	(0.0865)	(0.101)	(0.0684)	(0.0794)
N	*126*	*107*	*125*	*106*
R^2	0.409	0.460	0.222	0.331
Adjusted R^2	0.374	0.409	0.175	0.268

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: Author, 2022

Annex 12. Digital Divide Questionnaire

IHS
Making cities work
Erasmus

DIGITAL DIVIDE QUESTIONNAIRE

Today, many sources of information and various services are available online. This increasing digitalization affects different people in different ways. This survey is part of a larger research project about personal skills and usage of digital devices (such as computers and smartphones), the internet, and online services, as well as their benefits and limitations.

Below you will be asked to give your perception of various topics related to our research. With your answers, we will analyze who the digitalization of information and services affects and how it affects them. Some questions will be simple to answer, others you might be more uncertain about. Please answer to the best of your ability; we want to capture your main feelings and opinions.

Thank you for your help with this important project!

1. SOCIAL PERCEPTIONS

For the following statements, please rate your agreement from 1 (strongly disagree) to 5 (strongly agree).							
SOCIAL INCLUSION	1	2	3	4	5	N/A	Don't know
I consistently participate in my community (e.g., volunteering, cultural festivals, neighborhood meetings, etc.).							
I feel that my social needs, problems, and circumstances are considered by the municipality.							
PERCEPTION OF STEREOTYPES	1	2	3	4	5	N/A	Don't know
There are stereotypes about different kinds of people based on their identity (gender, ethnicity, etc.).							
I personally experience bias or discrimination because of my identity (gender, ethnicity, etc.) in my daily life.							
I personally experience bias or discrimination because of my identity (gender, ethnicity, etc.) in work or education.							
There are stereotypes about digital usage (of computers, smartphones, the internet) and abilities specifically related to a person's **gender**.							
I personally experience bias or discrimination regarding my digital usage and abilities because of my **gender.**							
There are stereotypes about digital usage (of computers, smartphones, the internet) and abilities specifically related to a person's **ethnicity**.							
I personally experience bias or discrimination regarding my digital usage and abilities because of my **ethnicity.**							

2. MATERIAL ACCESS

What types of devices do you have access to at home? (Check all that apply).

- ☐ Desktop computer
- ☐ Laptop
- ☐ Smartphone
- ☐ Tablet
- ☐ Other
- ☐ None

If applicable, how many of each device do you have at home?

- ☐ Desktop computer
- ☐ Laptop
- ☐ Smartphone
- ☐ Tablet

Do you have reliable access to an internet connection at home?

- ☐ Yes
- ☐ No

In the past 30 days, where have you used the Internet? (Check all that apply).

- ☐ At home
- ☐ At work, school, or university
- ☐ While traveling (e.g., on a bus, tram, or train)
- ☐ Somewhere else (e.g., library, internet café, at another person's house)

3. DIGITAL USAGE

I have an e-mail address.

- ☐ Yes
- ☐ No

How often do you use the internet?

☐ Never	☐ Less than once a week	☐ Once a week	☐ 2-3 days a week	☐ 4-6 days a week	☐ Daily

How often do you use online software or applications (Word, Excel)?

☐ Never	☐ Less than once a week	☐ Once a week	☐ 2-3 days a week	☐ 4-6 days a week	☐ Daily

In the past 12 months, for what purposes have you used the internet? (Check all that apply).

- ☐ Music/video streaming services
- ☐ Gaming
- ☐ Leisure internet searches (e.g., blogs, travel)
- ☐ Practical internet searches (e.g., recipes, childcare, healthcare)
- ☐ Online courses or training
- ☐ News (e.g., articles, videos)
- ☐ Finding/applying to jobs
- ☐ Online shopping
- ☐ Reading product reviews
- ☐ Social network sites
- ☐ Sharing photos/videos
- ☐ Other: ______________________

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4. SKILLS

For the following statements, please check yes or no according to your personal abilities.		
OPERATIONAL SKILLS	Yes	No
I know how to connect to a WIFI network.		
I know how to look for information online using a search engine.		
I know how to install apps on a mobile device such as a phone or tablet.		
I know how to download files and retrieve them once saved or stored.		
I know how to attach files to an email.		
I know how to complete online forms.		
I know how to avoid computer viruses.		

To what extent are the following statements true of you? Please answer from 1 (not at all true of me) to 5 (very true).							
INFORMATION SEEKING SKILLS	1	2	3	4	5	N/A	Don't know
I find it easy to decide the best keywords to use in online searches.							
I find it easy to use and navigate most websites.							
SOFTWARE/CONTENT CREATION SKILLS	1	2	3	4	5	N/A	Don't know
I know how to change the settings of a digital device or application.							
I know how to find, download, install, and configure applications.							
I know how to produce or edit content using a word processor (e.g., Word).							
I know how to produce or edit spreadsheets (e.g., using Excel).							
I know how to use basic formulas in a spreadsheet.							
I know how to create digital presentations (e.g., using PowerPoint, Canva).							
I know how to produce or edit simple digital content like images, memes, videos, and/or audio files.							
I know how to use specific software for design, calculation and/or simulation (e.g., Photoshop, AutoCAD, Aicon, etc.).							
SAFETY & SECURITY SKILLS	1	2	3	4	5	N/A	Don't know
I check if the information and websites I access online are trustworthy.							
I know which information I should and should not share online.							
I feel safe sharing my information online for services such as the municipality online portal or subscription websites.							

For the following statements, please rate your perception from 1 (low) to 5 (high).							
PROBLEM-SOLVING SKILLS	1	2	3	4	5	N/A	Don't know
My ability to solve routine problems with my devices (e.g., close program, restart computer, reinstall/update program, check internet connection) is:							
My ability to find support and assistance when a technical problem occurs or when using a new device, program, or application is:							
PERCEPTION OF DIGITAL INCLUSION	1	2	3	4	5	N/A	Don't know
Compared to others, my personal skill level using digital devices and/or the internet is							
My personal level of stress or anxiety about using digital devices and/or the internet is:							

For the following two statements, please rate your agreement from 1 (strongly disagree) to 5 (strongly agree).							
MOTIVATION/ATTITUDES	1	2	3	4	5	N/A	Don't know
Having access to the internet and digital devices has improved my life.							
My knowledge has increased because of the Internet (e.g., looking up information, talking to others online).							

5. FINANCE

For the following statements, please evaluate your personal usage frequency.							
DIGITAL FINANCIAL USAGE	Never	Rarely	Sometimes	Frequently	Always	N/A	Don't know
I use a digital bank account.							
I pay with a card or QR code (cashless).							
I use a digital financial app (e.g., Tikkie, Revolut, Bux).							
I use digital financial investments (e.g., stocks, cryptocurrencies).							

For the following statements, please check yes or no according to your personal perceptions.		
FINANCIAL ACCESS, USE, AND PERCEPTION	Yes	No
I find it easy to use digital financial solutions e.g., Tikkie, PayPal, split wise.		
I trust financial technology solutions such as Tikkie and Revolut.		
I look for interest rates and investment opportunities on the internet.		

How many digital bank accounts and/or wallets do you have?

In the past 5 years, I have applied for a loan (of any type or amount):

- ☐ Online
- ☐ At the bank branch
- ☐ I have not applied for a loan

6. LABOR

In the previous 12 months, what was your average household gross monthly income?

- ☐ €1350 or less
- ☐ Between €1350 and €1850
- ☐ Between €1851 and €2350
- ☐ Between €2351 and €2850
- ☐ Between €2851 and €3350
- ☐ Between €3351 and €3850
- ☐ Between €3851 and €4350
- ☐ Between €4351 and €4850
- ☐ Between €4851 and €5350
- ☐ More than €5350

What is your employment status? (Can check multiple)

- ☐ Full-time employed
- ☐ Part-time employed
- ☐ In education
- ☐ Caregiver
- ☐ Unemployed
- ☐ Retired
- ☐ Not looking for work

IF EMPLOYED, what type of contract do you have?

- ☐ Temporary
- ☐ Permanent
- ☐ Other: _________________

For the following statements, please select what is applicable to you.		
Please mark the occupations in which you are working now and/or in which you have worked in the last five years (multiple selections allowed).	**Current occupation** (mark only if you are currently employed)	**Last five years**
Building, craft, and related trade workers		
Plant machine operators and assemblers		
Sales, customer, or personal service workers		
Technicians		
Clerical support workers		
Skilled agricultural, forestry, and fishery workers		
Professionals		
Managers		

For the following statements, please select what is applicable to you.		
Please mark the sectors in which you are working now and/or in which you have worked in the last five years (multiple selections allowed).	**Current sector(s)** (mark only if you are currently employed)	**Last five years**
Agriculture, forestry, and fishing		
Manufacturing		
Electricity, gas, steam, and air conditioning supply		
Construction		
Wholesale and retail trade; repair of motor vehicles and motorcycles		
Transportation and storage		
Accommodation and food service activities		
Information and communication		
Professional, scientific, and technical activities		
Administrative and support service activities		
Education		
Human health and social work activities		

Considering your employment history, please answer the following questions.			
JOB STABILITY	Yes	No	N/A
In general, it has been difficult for me to find a job.			
In the past, I have had periods of unemployment.			
In the past, I have had difficulties finding a job because of my digital skills.			
I currently use digital devices in my job.			

7. **ONLINE SERVICES**

For the following statements, rate your agreement from 1 (strongly disagree) to 5 (strongly agree). Some municipal services include paying Council Tax, completing passport renewal, receiving a driving license, registering to vote, applying for public school.							
PERCEPTION OF MUNICIPAL SERVICES	1	2	3	4	5	N/A	Don't know
Most municipal services are offered online.							
I find online municipal services useful in my daily life.							
My interaction with online municipal services is clear and understandable.							
I prefer online services to in-person services.							
I would like to improve my ability to access online services.							

If the city of Rotterdam were to offer services for residents to improve their digital and internet skills, what format(s) would you prefer? (Check all that are of interest to you).

- ☐ Walk-in (no registration required)
- ☐ Requires prior registration

What type of assistance would you prefer?

- ☐ Once-weekly class (short – approx. 1 hour)
- ☐ Once-monthly workshop (long – approx. 2 to 4 hours)
- ☐ Office hours multiple times per week (open availability to ask someone for help)
- ☐ Other: ________________

What location would you prefer? (Check all that are of interest to you).

- ☐ Neighborhood school
- ☐ Local library
- ☐ Local religious center
- ☐ Community center
- ☐ Other: ________________

What days of the week would you prefer? (Check all that are of interest to you).

- ☐ Weekdays
- ☐ Weekends

What time frame would you prefer? (Check all that are of interest to you).

- ☐ Morning (9:00-12:00)
- ☐ Afternoon 12:00-15:00
- ☐ Late afternoon 15:00-18:00
- ☐ Evening 18:00-21:00
- ☐ Other: _______________

8. GENERAL INFORMATION

How old are you?

☐

What is your gender?

☐ Male ☐ Female ☐ Other ☐ Prefer not to say

How many children under the age of 18 live with you?

☐

What is your level of education (or equivalent)?

- ☐ Primary education
- ☐ Secondary education (VMBO, VWO, HAVO)
- ☐ Bachelor's degree – Vocational (HBO, MBO)
- ☐ Bachelor's degree – Academic (WO)
- ☐ Master´s degree or higher

What is your nationality? (Can list multiple).

What are your parents' places of birth?

Father	
Mother	

Do you have a DigiD?

☐ Yes ☐ No

In the past 12 months, have you used your DigiD to access any government services, information, etc.?

☐ Yes ☐ No

What is your native language? (Can list multiple).

IF YOUR NATIVE LANGUAGE(S) ARE NOT DUTCH OR ENGLISH,

Do you speak Dutch and at what level?

☐ Beginner ☐ Intermediate ☐ Advanced ☐ Fluent ☐ N/A

Do you speak English and at what level?

☐ Beginner ☐ Intermediate ☐ Advanced ☐ Fluent ☐ N/A

Are you registered with the Municipality of Rotterdam?

☐ Yes ☐ No

What is your zip code? (First four numbers only, e.g., 3073.)

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