Ph. D. Dissertation in Engineering

Study on the Dynamics of the Interrelationship between Technological Change, Tasks, and Skills of Workers

August 2023

Graduate School of Seoul National University

Technology Management, Economics, and Policy Program

Lee Hyejin

Study on the Dynamics of the Interrelationship between Technological Change, Tasks, and Skills of Workers

지도교수 **Jörn Altmann**

이 논문을 공학박사학위 논문으로 제출함
2023 년 8 월

서울대학교 대학원
협동과정 기술경영경제정책 전공
이혜진

이혜진의 공학박사학위 논문을 인준함
2023 년 8 월

위 원 장 ___이정동___ (인)

부위원장 ___**Jörn Altmann**___ (인)

위 원 ___구윤모___ (인)

위 원 ___홍아름___ (인)

위 원 ___**Heike Schröder**___ (인)

Abstract

Study on the Dynamics of the Interrelationship between Technological Change, Tasks, and Skills of Workers

Lee Hyejin
Technology Management, Economics, and Policy Program
The Graduate School
Seoul National University

Technological changes occur as a continuous and dynamic process relating to several factors, such as laws, regulations, industries, institutions, and workers within the socio-economic system. Therefore, revisiting existing approaches and constantly broadening the current perspectives regarding technology development is important. In this dissertation, technological changes in work and service are qualitatively studied, focusing on the relationships between technology and service and technology and work.

First, service classification is studied as a system of defining and categorizing services. Information technology generally affects services. Various services, such as platform services, have emerged with technological advancements. Therefore, the first research objective is to provide a service classification scheme identifying types of existing service

classifications and proposing new attributes, allowing for the characterization of platform services.

A systematic literature review is conducted to capture similarities between existing classifications and understand which attributes exist and how they can be classified into certain attribute types. The attributes from the analysis are applied to discuss whether existing attributes of service classification could cover emerging services. The case of platform services is analyzed to identify shortcomings in existing attribute types. The existing classifications are insufficient to describe platform services because they do not address changes for new businesses or technologically transformed processes. Based on the results of this analysis, a comprehensive list of attribute types for existing service classifications and additional attribute types for platform services are proposed. These attribute types can help describe various services and account for transitions resulting from technological advances.

As much as technology can change the shape of industries, this alteration also affects the people who work in them. Accordingly, considering related factors should improve the description of technological changes. Technology can accomplish tasks, and workers could be displaced from these tasks. Further, there are possibilities that new tasks could be created in which human labor has comparative advantages compared with machines, which may lead to new hires and increased employment. However, skill changes due to technological changes compared with tasks have received little attention in the literature. Therefore, the second research objective is to understand transformation within an occupation by observing the changes in skills and tasks. The case of cashiers is investigated to understand this transformation. The skills and tasks of cashiers have changed to focus on more interactive, cognitive, and social elements. Social skills have received more attention in an era where these tasks cannot be easily performed by computers and machines. Focusing on one occupation through the case study of cashiers allows for a deeper understanding of the changes within it.

Following the case study of cashiers, the skills required to perform tasks are analyzed further. The flow of changes in skills within and across occupations is analyzed to study the existing skills and those that have become more important over time. The third research objective is to investigate skills and their changes across several occupations. Thirty-seven occupations are examined, and the study confirms that most skills have changed over time. In addition, skill changes are analyzed according to skill-related factors, such as the formal education level. Social skills for all occupations reveal significant changes, and negotiation and persuasion have become more meaningful over time. The study classifies skill elements into tacit and explicit knowledge types to explore skill changes and address the limitations of conventional methods of defining skills. Through the analysis of the results, this study presents a model that can capture and explain skill changes.

In summary, this thesis attempted to understand the dynamics of the interrelationship between technological change, tasks, and skills of workers using the qualitative research approach, beginning with the importance of studying the transformation caused by technological development from a different perspective. This was accomplished by

studying technological changes in work and in services to understand how they respond to technological changes and how changes in them can be explained. Furthermore, this study revealed that qualitative analysis could be a meaningful approach, demonstrating that qualitative research methods using descriptive data can grasp the details of organic and continuous changes and understand their overall flow.

Keywords: Technological change, Skill, Task, Worker, Labor, Service classification
Student Number: 2014-31108

Contents

List of Tables

List of Figures

Chapter 1. Introduction

1.1 Research background

Technological changes occur as a continuous and dynamic process by relating various factors, such as laws, regulations, industry, institutions, and labor, within a socio-economic system. The discussion of this topic has progressed over time. By focusing on relations between technology and economic development, a pattern of technological changes emerges while solving technological problems (Dosi, 1982), and new technology extensively influences all economic sectors (Perez, 1983, 2010). To explain further how technology development relates to other technology clusters, institutes, social systems, and policies, a multi-level perspective is suggested that describes socio-technical systems' changes and transitions followed by technology development (Geels, 2002, 2004). This approach explains what happens between innovation and socio-technical transitions, but there remains little explanation of how and why changes have taken specific paths. To describe patterns of how socio-economic systems respond to technological changes and how such a series of transformations can be explained, an analytical framework of technology induced transformation is proposed (Dolata, 2009, 2013). Dolata's framework describes, first, the direct and indirect effects of new technology; second, sectoral responses to new technology; and third, continuous changes as a result of the interplay between the two concepts. Technology-based changes cause a series of restructuring processes and sectoral changes in the long term (Dolata, 2009). As like this, extensive studies have revealed that technological changes occur organically and continuously, with related factors in socio-economic systems.

1.2 Problem description

Certain changes become widespread due to information technology (IT), digital devices, and network effects. For example, IT generally has a major impact on transforming how value is delivered in services (Gallouj, 1997; Zysman, 2006), and, with its advancement, a different type of service has emerged from traditional services, such as platform-based businesses. A platform is a center for connections between providers and customers, and its development is based on an information and communication technology (ICT) infrastructure, comprising software, ubiquitous networks, and computing power (Haile & Altmann, 2016a, 2016b). Technological availability makes a platform business capable. Through platform businesses, customers and providers join to conduct economic transactions without significant barriers (Choudary, Van Alstyne, & Parker, 2016). Platform services have the potential to alter the shapes of industries. One of the major issues that arises from rapidly growing platform businesses concerns the identification of platform services in the traditional industry service classification. These services have disrupted the existing industry in the same was as Uber, Zipcar, Lyft, and Airbnb, and they have shaken up by reorganizing previously less organized services, such as TaskRabbit, Handy, and Upwork (Kenney & Zysman, 2015; Zysman & Kenney, 2017). Different standpoints regarding identifying the platform business between institutions and businesses in terms of disruptions and shake-ups exist. These different standpoints are found in two legal cases related to Uber from the United States (US) and the European Union (EU),[1][2] revealing problems caused by the distinction between the two. The main argument concerned whether the company provides transportation or technology. Uber claims to be a technology company in the IT field, providing technology; hence, Uber drivers are independent contractors. According to how Uber defines itself, Uber driver's employment conditions are either an independent contractor or an employee of Uber. The existing classification seems to have limitations regarding flexibly reflecting new services based on technological changes. It is necessary to broaden the perspective with constant technological development by revisiting existing approaches for investigating whether existing service classification can cover emerging services properly.

---

1 O'Conner v. Uber Technologies, Inc., Case3:13-cv-03826-EMC (US Northern District of California, 2015).

2 Asociación Profesional Élite Taxi v. Uber Systems Spain SL, ECLI:EU:C:2017:981, Judgement of the Court (Grand Chamber) in Case C-434/15 (EU Court of Justice, 2017).

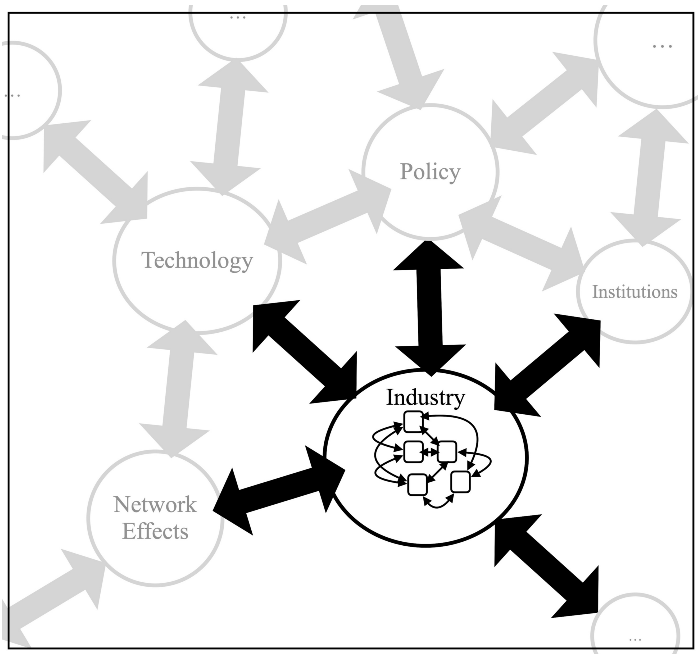


Figure 1.1 Overview of problem description

As much as technology can change the shape of industries, their alteration affects the people within them. Change is interrelated to factors. The above Uber-driver case illustrates that employment conditions are one issue that needs to be considered. Furthermore, technology can change the work people perform. The impacts of the continuous advancement of technology on labor have been discussed in various ways. In previous studies, their approaches and conclusions differ from the research focuses. For instance, Frey and Osborn (2017) analyzed jobs at risk by focusing on the technological capabilities of replacing certain tasks. The researchers conclude that about 47% of US employment is susceptible to automation in the near future. Arntz, Gregory, and Zierahn (2017) discuss tasks in occupations that can be automated, concluding that this does not mean these occupations are at risk of being replaced by automation. The researchers view an occupation as being composed of many different tasks, and technologies can replace these tasks rather than the occupation. According to Arntz et al. (2017)'s estimation, 9% of US jobs are at high risk of automation. Regardless of size, tasks and occupations are facing changes (displacement) by technology. The literature argues that technology changes work. If tasks are substituted through technology, workers could be displaced. On the other hand, new tasks can be created for which human workers have comparative advantages compared with machines, which may lead to new and increasing employment (Acemoglu & Restrepo, 2017, 2018c; Autor, 2015; Bessen, 2015; Vermeulen, Kesselhut, Pyka, & Saviotti, 2018). New technologies can have both negative and positive effects. Based on research perspectives, data, and methodology, the literature reaches different conclusions, which is an inevitable process of understanding change. Nevertheless, as Dosi and Virgillito (2019) highlight, research approaches in studies have been limited by focusing on relatively direct relationships between jobs and machines and missing that transformations occur collectively through cooperation between actors in organizations (Dosi & Virgillito, 2019). Transformations caused by technological development should be interpreted and studied in various contexts, such as changes in the relationships between labor, work, and skills.

Previous studies (Dosi, 1982; Geels, 2002, 2004; Perez, 1983, 2010) have focused on the technological changes incurred. Essentially, such research begins with technology and analyzes directly relevant factors, such as industries, organizations, institutions, and policy. However, it becomes more difficult to tell which changes are caused by a specific technology. Since changes occur by interrelating between relevant factors. Previous studies have discussed how socio-economic changes occur: first, as a whole, through direct and indirect effects in general (Boyd & Holton, 2018); second, collectively, through collaborations of members within organizations (Dosi & Virgillito, 2019); and third, as a result of combining technological and organizational transformation (Cirillo, Rinaldini, Staccioli, & Virgillito, 2021). As Dolata (2009, 2013) highlights, technological changes in society are extensive, interrelated, and occur simultaneously. Figure 1.1 provides an example of these various factors and their connections. The size or position of the circle in the figure does not indicate the importance of the factor; the figure attempts to express visually the relationship discussed above and emphasize that it is important to study current technological change from the perspective of these factors being interconnected and dynamically affecting each other. Understanding correlations is important because of the rapid development of artificial intelligence (AI) and to determine institutional changes and supports. Therefore, how existing industrial classification can cover rapidly growing businesses and how work is changed are related issues to discuss differently from previous standpoints.

When technology can change services with new processes and products (Figure 1.2), the impact should be related to people and work within services, and when technology can replace or displace tasks in occupations, the response of workers to the change should be considered in skill changes. As such, technological changes occur as a continuous and dynamic process by relating various factors within a socio-economic system.

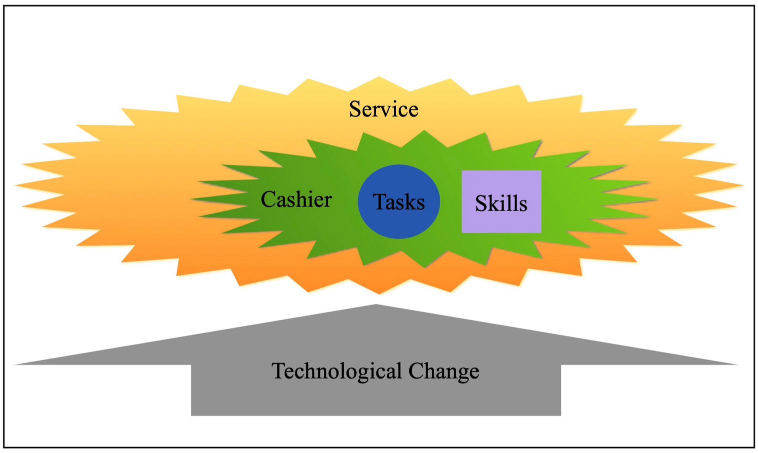


Figure 1.2 Overview of the topics addressed in this thesis

1.3 Research questions

This thesis studies technological changes in work and in services via three main research questions:

1) How are services impacted by technological changes?

2) How do tasks and skills respond to technological changes, and how can changes in tasks and skills be explained?

3) How could skill changes be described and captured in an analytical framework?

To answer these research questions, a qualitative research methodology was used for analysis. Qualitative research methods involve observations and indications rather than quantitative datasets. There are three major reasons to use a qualitative approach: first, it provides a way of building a theory based on observations and findings; second, it provides an opportunity to understand society by investigating how its participants perceive it; and third, it expresses a reality that is constantly changing through individuals' actions (Bryman, 2012). This qualitative approach answers the three main research questions are as follows: First, the approach investigates the transformation of describing and classifying services via technological changes, and a service classification scheme is proposed. Specifically, the concept of service is focused on a consideration of new businesses appearing and spreading based on digital technology, such as platform businesses, as discussed previously. The concept of classification is studied as a system of defining and categorizing services. A systematic literature review was conducted. This research method is appropriate because it can facilitate theory development by combining various research topics and revealing unidentified research objects (Webster & Watson, 2002; Whetten, 1989). Second, the approach examines how technology impacts labor skill changes within and across occupations. Two case studies were conducted to understand the relationship between work and technology. A case study enables a case to be investigated in depth (Bryman, 2012) and can especially be adopted when 'how' and 'why' questions are raised, when circumstances for the research are difficult to control, and when the object is to present a real-life situation (Yin, 2014).

1.4 Overview

This thesis consists of five chapters including this first chapter, the introduction (Figure 1.3). Chapter 2 begins by analyzing common attributes describing existing services. Examining the case of platform services helps to determine whether existing attributes of service classification are suitable for comprehending new services. Then, an extended classification with new attributes is proposed to explain changes in service, followed by an observation of how technological changes affect work and skills. The first case study of cashiers, analyzes changes in tasks and skills within one occupation in Chapter 3. In Chapter 4, a second case study verifies specific skills that have become more important over time. From these two case studies, changes in work within and across occupations are described, and a framework is proposed for representing skills to account for salary and productivity. Chapter 5 concludes with a summary of the findings and a discussion, including the implications of the findings and for future research.

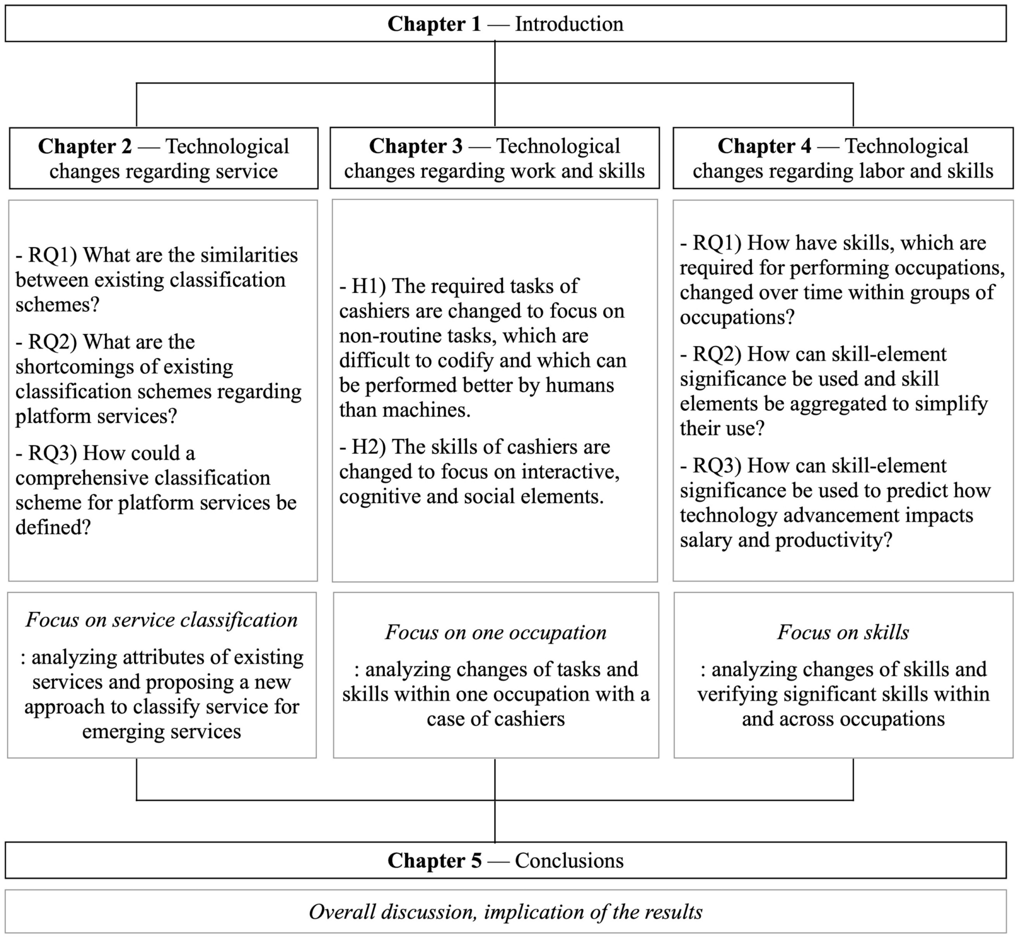


Figure 1.3 Overview of the thesis

Chapter 2. Service Classification Scheme for Platform Services

2.1 Introduction

2.1.1 Research background

Industry classification is the process of classifying industries based on what they have in common, according to certain criteria (Dalziel, 2007; Peneder, 2003). The International Standard Industrial Classification of All Economic Activities (ISIC) and the North American Industry Classification System (NAICS) categorize industries based on productive activities. The ISIC is the United Nations (UN) classification of production activities. The system was created as a reference for collecting statistical data on economic activities, was first applied in 1948, and is currently revised up to 2008 which is ISIC rev.4 (UN, 2008). The NAICS replaced the Standard Industrial Classification (SIC) in the United States in 1997 and was developed by the US, Mexico, and Canada to classify production activities in North America (U.S. Census Bureau, 2022). It has been pointed out that this economic activity-oriented classification does not reflect the actual industrial structure, and that there are industries that are not measured, leading to the proposal of a classification that reflects changes in industrial structure (Dalziel, 2007; Hicks, 2011). In the field of technology innovation, Pavitt's taxonomy, which categorizes industries according to their technological regime, is also well known (Pavitt, 1984). Industry classifications have been developed and used in a variety of ways, depending on the actors involved, the purpose of the classification, and the region in which they are employed (Phillips & Ormsby, 2016). Industry classifications also vary depending on the field of study (Peneder, 2003). This factor is especially obvious regarding classifying services. Previous studies have discussed services and categorized them differently across perspectives and disciplines.

Research has described the concept of services in many ways. Judd (1964) defines services as market transactions. According to Hill (1977), services represent “a change in the conditions of a person or a good belonging to some economic unit” (p. 318). Mills and Turk (1986) describe a service as “a performance or an effort rendered by one party for another” (p. 92). Other scholars have considered services as performances and processes (Grönroos, 1988; Lovelock & Patterson, 2015, p. 7). Vargo and Lusch (2004) provide a comprehensive definition of services as “the application of specialized competencies (knowledge and skills) through deeds, processes, and performances for the benefits of another entity of the entity itself” (p. 2). In addition, Rathmell (1966) explains services by distinguishing goods and services, and Edvardsson (1997) views services as a “part of the wider concept product” (p. 33). As is evident from this brief review, the definitions of services address different aspects in different research fields.

Service classifications have been considered in marketing (Bitner, 1992; Carlborg & Kindström, 2014; Cunningham, Young, Lee, & Ulaga, 2006; Lovelock, 1983; Price, Arnould, & Tierney, 1995), the service industry and business management (Henneberg, Gruber, & Naudé, 2013; Liu & Wang, 2008; Schmenner, 1986; Silvestro, Fitzgerald, Johnston, & Voss, 1992), operation studies (Cook, Goh, & Chung, 1999; Kelley, Donnelly,

& Skinner, 1990; Mersha, 1990; Wemmerlöv, 1990), and economics (Gadrey, 2000; Hill, 1977, 1999). As the definition of service differs depending on the aspects of research fields, its classification also differs depending on related disciplines. In general, marketing and operation studies discuss service classifications and characteristics to develop and improve delivery processes. Economics studies focus more on outputs to understand and distinguish between goods and services.

Although most existing classifications have been discussed to provide strategic and managerial implications, it is difficult to use them empirically (Glückler & Hammer, 2011). This difficulty is caused by existing service classifications mostly being derived from conceptual and theoretical approaches. To overcome this problem, a few studies (e.g., Glückler and Hammer, 2011; Shafti et al., 2007) have reviewed the literature to find a solid classification model that could be adopted across services, and combined their literature review with their empirical data.

2.1.2 Problem description

If services are classified in different ways according to fields, one limitation concerns defining new services. Recently, new services have emerged through platform-based businesses. A platform is a center for connections between providers and customers, and its development is based on an ICT infrastructure, comprising software, ubiquitous networks, and computing power (Haile & Altmann, 2016a, 2016b). One well-known platform business is TaskRabbit. The company connects providers who offer their labor to customers who need help with everyday tasks, such as cleaning, moving, and assembling furniture.[3] Through platform businesses, customers and providers can conduct economic transactions freely and without any barriers. The technological availabilities of software, distributed computing, and the internet make a platform possible (Choudary et al., 2016). As platform businesses have the potential to change the shapes of industries and even affect entire economic structures, it is highly relevant to check whether existing service classifications can cover these services properly.

2.1.3 Research objective

Following this discussion on service classification, emerging platform businesses in services and their relevance, the research objective is to provide a comprehensive list of characteristics of service attributes for service classification by identifying the service types of existing service classifications and by proposing new attributes that allow characterizing services of platforms. To help achieve this research objective in this chapter, the research questions are as follows:

RQ1) What are the similarities between existing classification schemes?

RQ2) What are the shortcomings of existing classification schemes regarding platform services?

RQ3) How could a comprehensive classification scheme for platform services be defined?

[3] Official website of TaskRabbit (https://www.taskrabbit.com/about)

To answer the research questions, a systematic literature review was conducted to capture the similarities between existing classifications. Since services and service classifications have been defined differently by related disciplines, such as marketing, operations, and management, it is necessary to employ a methodology that can integrate multiple perspectives to analyze them. For this, a systematic literature review is suitable for analyzing a research subject that is studied diversely in different research fields. In addition to a systematic literature review, there are other methodologies for analyzing literature or text, such as meta-analysis, keyword analysis, and text analysis. However, other methodologies for analyzing literature or text have some limitations to analyze a subject defined differently in diverse fields. For example, meta-analysis uses literature as data to collect and examine the results of studies published on similar topics in a limited research area (Donthu, Kumar, Mukherjee, Pandey, & Lim, 2021), or text analysis uses the text need to be necessary to be similar or from the same root of the word to be processed as data (Lucas et al., 2015). Therefore, a systematic review that uses literature and data from various studies was considered suitable for analyzing services that are defined and categorized in many ways in different fields.

A systematic literature review provides a way to integrate diverse research topics (Webster & Watson, 2002; Whetten, 1989), so it is useful for analyzing similarities and differences. For example, similarities and differences have been analyzed to identify characteristics of defining service innovation from different perspectives (Witell, Snyder, Gustafsson, Fombelle, & Kristensson, 2016) and categories of service innovation (Snyder, Witell, Gustafsson, Fombelle, & Kristensson, 2016). In addition, similarities and differences between service classifications have been analyzed to develop a useful service classification for managers by combining existing classifications from a systematic review of articles between 1997 and 2013 (van der Valk & Axelsson, 2015). Furthermore, service definitions and classifications from literature dating from the 1960s to the 1990 have focused on the areas of organization, marketing, and operations (Cook et al., 1999). Therefore, a systematic literature review was employed to answer three research questions in this chapter and was appropriate for proposing a comprehensive classification scheme.

The study by Cook et al. (1999) was chosen as the basis for searching for further journal articles, as it is considered a good starting point for studying service definitions and classifications in the literature from the 1960s to the 1990s. Their research focuses on organization, marketing, and operations but does not analyze literature from the 2000s onward. Considering this limitation, this present study employed Cook et al. (1999) as an important reference for literature searches but did not limit the field and included literature from the 2000s onward. The search list was extended by conducting a forward citation search on the Web of Science (WoS). Additional papers between 2000 and 2017 that developed classification schemes were determined. From this literature review process, an understanding of which attributes exist and how they can be grouped into attribute types was obtained. To identify the shortcomings of these attribute types, a use case of a platform business that offers platform services was explored.

This analysis provides a comprehensive list of attribute types of existing service classifications and a list of additional attribute types for platform services. These attribute types can help to describe different service types and explain transitions caused by technological developments.

The remainder of the chapter is organized as follows: Section 2.2 provides an overview of services and service classifications from previous studies. Section 2.3 describes the research methodology and findings from this study's analysis. A case study is introduced in Section 2.4 and discussed in Section 2.5. Finally, Section 2.6 concludes the study with a discussion of limitations and future research.

2.2 Existing research directions regarding services

2.2.1 Service theories

One notable theory of services in marketing defined the service-dominant logic (S-D logic), which considers a service to be "a process of doing something for another party" (Vargo & Lusch, 2008, p. 255) and a customer as "a coproducer" of service (Vargo & Lusch, 2004, p. 10). By moving the goods-centered perspective of marketing into a service-dominant view, Vargo and Lusch (2004) determine value of services differently than in a goods-dominant logic (G-D logic). In traditional G-D logic, value is determined by value-in-exchange, whereas S-D logic defines it as value-in-use (Vargo & Lusch, 2004). Therefore, service is viewed as a value co-creation by all involved actors in the logic (Vargo & Lusch, 2008).

Another study of operation management defined the unified service theory (UST), which considers a customer as a significant input in the process of production (Sampson & Froehle, 2006). Furthermore, the UST has managerial implications for production and extends customer roles in the service supply chain. Overall, S-D logic and the UST are important, as they consider customers to be co-creators and co-producers of services.

2.2.2 Service characteristics

Four characteristics have been commonly known as natures of services: intangibility, heterogeneity, inseparability, and perishability. These characteristics are called IHIP (Fisk, Brown, & Bitner, 1993; Lovelock & Gummesson, 2004). Typically used in service research, IHIP have a few limitations (Edvardsson, Gustafsson, & Roos, 2005; Moeller, 2010). First, although intangibility relates to services not being physically visible as goods (Edvardsson et al., 2005), the characteristic, intangibility, is criticized because some services (e.g., teaching) become entangled with tangible goods, such as teachers, books, and classrooms (Lovelock, 1983; Moeller, 2010). Second, since heterogeneity concerns services that vary regarding service operations and customer experiences, it does not reflect the difficulties concerning standardization through technology and equipment (Lovelock & Gummesson, 2004; Moeller, 2010). Third, inseparability involves simultaneous production and consumption. However, there are separable services that permit customer absences at production, such as laundry and the maintenance of equipment and facilities (Lovelock & Gummesson, 2004). Finally, perishability means services cannot be stored. The following service definitions illustrate that services are processes and performances (Rathmell, 1966).

However, the example of automated teller machine (ATM) is frequently mentioned, as these involve a standardized process of cash withdrawal (Edvardsson et al., 2005; Gummesson, 2000; Moeller, 2010).

2.2.3 Service classifications

In previous research, service classifications have been studied and proposed by focusing on a few service-related factors. Customer contact has been considered important for classifying services. Chase (1978, p. 138) proposes the customer contact model, which involves the customer's physical presence in service creation and classifies services into four groups: pure service, mixed service, quasi-manufacturing service, and manufacturing service. Other traditional service studies have adopted this model to explore service organization designs (Chase & Tansik, 1983), and it has been extended by considering how communication technology affects contact time (Mersha, 1990). Wemmerlöv (1990) presents a framework with customer contact levels and service process characteristics that are rigid or fluid.

Regarding processes, Chase (1978, 1981) defines customer contact as the customer's presence, whereas Schmenner (1986, 2004) discusses how customers may have little interaction with service providers in processes, even if they are present physically. Schmenner (1986, 2004) proposes a service process matrix with a degree of customer interaction and customization and a degree of labor intensity. In addition, Silvestro et al. (1992, p. 67) point out that service contact could consist of two elements as frequency and duration. Regardless of the perspective on the physical presence of customers during services, one significant classification of services is based on customer contact.

Other studies have adopted on a customer-centered perspective and considered performed actions for classifying services. For example, Lovelock (1983) and Kelley et al. (1990) mainly focus on the level of customization and the nature of service actions. Other studies have captured how customers recognize and classify services (Cunningham, Young, & Gerlach, 2008; Cunningham, Young, & Lee, 2005; Cunningham et al., 2006; Cunningham, Young, Ulaga, & Lee, 2004). In addition, there is a mathematical model of provider, process, place, and customer (Liu & Wang, 2008; Liu, Wang, & Lee, 2008). A range of service activities have been distinguished (Zysman, Murray, Feldman, Nielsen, & Kushida, 2011), and a new definition of service networks has been proposed by identifying relations between actors in the service context (Altmann, Meschke, & Bany, 2012). Furthermore, Maglio, Srinivasan, Kreulen, and Spohrer (2006) focused on the values created from relationships between providers and customers, and Henneberg et al. (2013) identified service networks from relationships between services and products.

Although previous studies have taken various approaches classifying services, their service classifications are mostly suggested conceptually and would not be sufficient to embrace anything other than their own domains. This study proposes and provides attributes to describe existing and new services by offering a common understanding obtained through research on the similarities and differences between existing models, regardless of the research focus or field. A framework is provided that explains changes in services and industries.

2.3 Toward a consolidated classification scheme unifying existing service classification

2.3.1 Methodology and data collection

Services have been defined and classified differently depending on their foci, meaning a systematic literature review is a useful method for discovering unrecognized aspects and address current trends in a more inclusive service classification scheme compared with existing service classifications. A systematic literature review can facilitate theory development, combining various research topics, and revealing unidentified research objects (Webster & Watson, 2002; Whetten, 1989). Webster and Watson (2002) provide a guideline for writing a literature review and recommend three steps to determine review materials: first, find major contributions from leading journals; second, find articles by checking the references of the articles identified in Step 1 (going backward); and third, find articles by checking the citations of the articles identified in Step 1 using WoS (going forward).

Following Webster and Watson (2002), this present research explored well-known service studies regarding service classification schemes (Figure 2.1). Among these studies, Cook et al. (1999) provide the most comprehensive perspective on the topic. Although the paper provides a fine basis that can lead to major literature on service classifications, it includes studies only until the 1990s. To find more recent studies, journal papers were identified using the forward citations of major studies listed in Cook et al. (1999) on WoS. The website was used to search for articles, as Webster and Watson (2002) recommended.

Forward citation searches were conducted to find direct connections between frequently used studies and more recent studies. In total, 1,126 journal articles were found from the year 2000 onward. The abstracts, keywords, and research fields of those journals were examined. Eighty-four articles were considered for detailed analysis regarding service classifications. By examining the full papers of these 84 articles, the analysis revealed that 19 studies developed and proposed their own classification schemes. Overall, 35 articles were collected to be examined in this study. Of those 35 articles, 16 were from the 1960s~1990s and 19 from the 2000s~2010s.

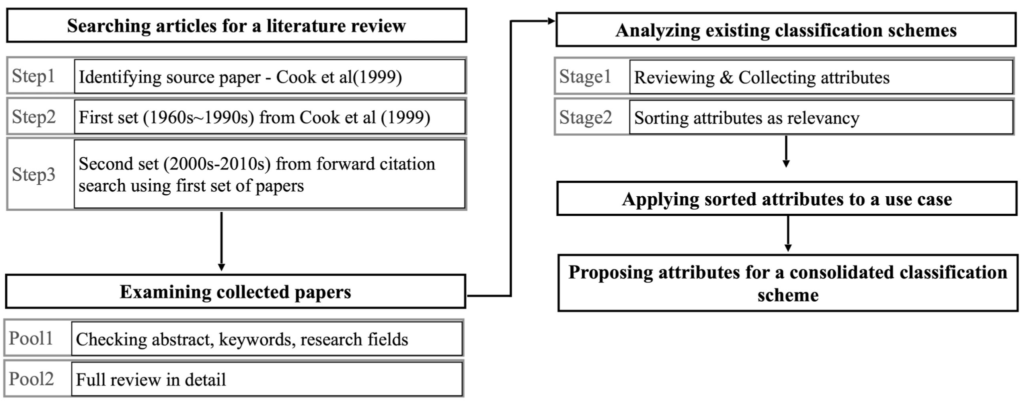


Figure 2.1 Research framework

2.3.2 Analysis of attributes used in existing classification schemes

Based on the 35 articles about service classifications, the attributes used to classify and segment services were analyzed. These attributes were reviewed regarding relevancy and similarity and categorized into attribute types. For example, attributes such as contact, customer contact, client contact, degree of contact, and contact intensity were classified as the general type 'degree of customer contact.'

Table 2.1 reveals that classifications from 13 studies have used an attribute to reflect customer contact. The attributes mostly followed an identical notion of Chase (1978), which describes a customer's physical presence in a service creation. These attributes have grouped under the attribute type 'degree of customer contact'.

The attribute type 'degree of customization' contains attributes of 11 classifications that addressed the concept of altering processes to meet customer needs in services and that described the level of modification of services.

Table 2.1 List of attribute types

Attributes	#	Literature
Degree of customer contact	13	Chase (1978), Maister & Lovelock (1982), Lovelock (1983), Haywood-Farmer (1988), Bowen (1990), Mersha (1990), Wemmerlöv (1990), Silvestro et al. (1992), Cunningham et al. (2005), Shafti et al. (2007), Theotokis et al. (2008), van der Valk & Axelsson (2015), Jaakkola et al. (2017)
Degree of customization	11	Maister & Lovelock (1982), Lovelock (1983), Schmenner (1986), Haywood-Farmer (1988), Bowen (1990), Silvestro et al. (1992), Cunningham et al.

		(2005), Shafti et al. (2007), Cunningham et al. (2008), Liu & Wang (2008), van der Valk & Axelsson (2015)
Service process	10	Lovelock (1983), Zvegintzov (1983), Wemmerlöv (1990), Silvestro et al. (1992), Kellogg&Nie (1995), Buzacott (2000), Cunningham et al. (2005), Johansson & Olhager (2006), Carlborg & Kindström (2014), van der Valk & Axelsson (2015)
Object of service	9	Murphy & Enis (1986), Silvestro et al. (1992), Kellogg & Nie (1995), McDermott et al. (2001), Cunningham et al. (2005), Liu & Wang (2008), David (2014), van der Valk & Axelsson (2015), Cusumano et al. (2015)
Service characteristics (IHIP)	9	Lovelock (1983), Murphy & Enis (1986), McDermott et al. (2001), Cunningham et al. (2005), Shafti et al. (2007), Cunningham et al. (2008), van der Valk & Axelsson (2015), He et al. (2016), Jaakkola et al. (2017)
Degree of application /implementation	9	Thomas (1978), Silvestro et al. (1992), McDermott et al. (2001), Wynstra et al. (2006), Theotokis et al. (2008), Liu & Wang (2008), Glückler & Hammer (2011), van der Valk & Axelsson (2015), Jaakkola et al. (2017)
Labor intensity	9	Thomas (1978), Mills & Margulies (1980), Schmenner (1986), Haywood-Farmer (1988), Silvestro et al. (1992), Shafti et al. (2007), Lee & Park (2009), Wünderlich et al. (2013), Roels (2014)
Degree of interaction	7	Mills & Margulies (1980), Schmenner (1986), Haywood-Farmer (1988), Cunningham et al. (2005), Shafti et al. (2007), Roels (2014), van der Valk & Axelsson (2015)
Degree of standardization	7	Bowen (1990), Buzacott (2000), Cunningham et al. (2008), Liu & Wang (2008), Roels (2014), van der Valk & Axelsson (2015), He et al. (2016)
Customer participation	6	Larsson & Bowen (1989), Shafti et al. (2007), Wünderlich et al. (2013), Carlborg & Kindström (2014), Roels (2014), van der Valk & Axelsson (2015)
Diversity	4	Shostack (1987), Larsson&Bowen (1989), Glückler & Hammer (2011), van der Valk & Axelsson (2015)
Place	3	Silvestro et al. (1992), Shafti et al. (2007), Liu & Wang (2008)
Complexity	3	Shostack (1987), van der Valk & Axelsson (2015), Jaakkola et al. (2017)

Volume	2	Johansson & Olhager (2006), Lee & Park (2009)
Judgment	2	Cunningham et al. (2005), Shafti et al. (2007)
Convenience	1	Cunningham et al. (2005)
Contingency	1	Liu & Wang (2008)
Riskiness	1	Cunningham et al. (2005)
Switching	1	Cunningham et al. (2005)

Variations of the attribute type 'service process' were found in 10 classifications of studies, covering distinct qualities of delivery and processes. Most of the classifications discussed service processes under the assumption of physical contact between customers and providers.

Nine studies considered the results of services in their classifications, covering the outcomes customers receive from services, and these were categorized as the attribute type 'object of service.'

'Service characteristics (IHIP)' comprise attributes about the nature of services. These attributes, which were mentioned nine times in the classifications, are subsets of IHIP.

Attributes concerning the utilization of technology, knowledge, and equipment in services were grouped into nine classifications of attributes named 'degree of application and implementation.'

The attribute type 'labor intensity' concentrates on service provider activities and how services depend on individual workers. This classification was used in nine studies.

Four of the studies that used labor intensity also considered the depth of interactions between customers and providers. In total, seven studies applied this notion, which was labeled ‘degree of interaction.’

An attribute regarding the level of routinization and standardization was found more frequently in the literature after 1990. Seven classifications considered this attribute type, which was named ‘degree of standardization.’

With the increasing attention on customer role in services since the year 2000, six classifications considered the attribute type 'customer participation,' which describes customer activities and roles in joining services.

Four classifications focused on attributes about the variety of customer demands. This attribute type was labeled ‘diversity.’

Although expressed differently, three classifications followed a very similar concept of ‘place,’ expressing a focus on service being in the front office, back office, or virtual space.

The attribute type ‘complexity,’ in three classifications, describes the complexity of providing a service.

The remaining attribute types (i.e., volume, judgment, convenience, contingency, riskiness, switching) all appeared fewer than three times and were considered unique qualities in each study.

2.4 Application of attribute types to a use case

2.4.1 Case description: TaskRabbit

TaskRabbit is a company founded in 2008 that connects platform users of taskers (willing to provide labor) and customers (who need help with tasks, e.g., cleaning, moving, assembling furniture). TaskRabbit, which advertises itself as a ‘same-day service platform,’[4] can be considered a platform service provider. TaskRabbit is useful as a case study, because its service require no tangible products and does not involve complex transactions between its users (Isaac, 2015; Prassl & Risak, 2015).

With the help of the attribute types listed in Table 2.1, the service of TaskRabbit is described in detail. To establish connections between customers and taskers, TaskRabbit's platform users do not need to be physically present when the transactions on the platform happen. Therefore, it is difficult to measure customer contact between TaskRabbit and users. TaskRabbit provides information and connections using standardized processes to both types of platform users. The platform also provides customized services since its users can decide on the service and its provisioning according to their particular needs. In addition, as TaskRabbit is a platform that connects both types of users, a relationship between a customer and a tasker can hardly be defined as unidirectional. Moreover, it is not only difficult to measure the degree of contact but also the degree of interaction. Furthermore, as customers are provided labor for their needs by taskers who are hired temporarily by TaskRabbit, TaskRabbit can be rated as having high 'labor intensity.'

[4] Official website of TaskRabbit (https://www.taskrabbit.com/about)

2.4.2 Applying the attributes of the classification scheme to the case of TaskRabbit

Based on the consolidated classification scheme structured with the attributes analyzed in the previous section (Table 2.1), the service of TaskRabbit can be described. Attributes that appeared more than three times in Table 2.1 were applied to TaskRabbit. Describing the case using attributes meant examining whether each attribute could explain the case (Explainable), could explain the case partially depending on conditions (Half explainable), or could not explain the case (NOT explainable; Table 2.2). Of the 13 attributes on the list, five could be used to explain TaskRabbit, another five could not explain TaskRabbit, and three could partially explain the case.

Table 2.2 Applying attributes to TaskRabbit

Attributes (appeared more than three times)	**Applying to TaskRabbit**	
Degree of customer contact	NOT explainable	The attribute requires physical contact or presence in transactions: it cannot explain the case.
Degree of customization	Explainable	Platform users can decide on the service and its provisioning according to their particular needs: it can explain the case.
Service process	NOT explainable	The attribute is discussed under the assumption of physical contact between customers and providers: it cannot explain the case.
Object of service	Explainable	The attribute describes the outcomes customers receive from services: it can explain the case.

Service characteristics (IHIP)	Half explainable	The attribute includes intangibility, heterogeneity, inseparability, perishability: mainly two, inseparability and perishability cannot be applied to the case.
Degree of application /implementation	Explainable	The attribute concerns the utilization of technology, knowledge, and equipment in services: it can explain the case
Labor intensity	Half explainable	According to the study's definition, 'labor intensity' concentrates on service providers' activities and how services depend on individual workers. It depends on who the service provider is in the case: it can explain the case partially, depending on whether defining a service provider as TaskRabbit providing the platform service or a service provider as a tasker providing labor.
Degree of interaction	NOT explainable	The attribute requires physical presence or contact: it cannot explain the case.
Degree of standardization	Explainable	TaskRabbit provides information and connections using standardized processes to both types of platform users: it can explain the case.
Customer participation	Half explainable	The attribute describes activities and roles for joining services: it can explain the case partially, depending on whether defining a customer as a tasker using the platform or a customer as a user requesting labor.
Diversity	Explainable	The attribute describes the variety of customer demands: it can explain the case.
Place	NOT explainable	The attribute expresses a focus on a service being in the front office, back office, or a virtual space: it cannot explain the case.
Complexity	NOT explainable	The attribute is concerned with the complexity of providing a service under the assumption of physical contact: it cannot explain the case.

2.4.3 Analysis results from applying attributes to the case

Three dimensions could not describe the case of TaskRabbit. These attributes are closely related to physical contact or the presence of either the service provider or the customer.

First, existing classification schemes assume that service processes require physical contact between customers and providers (Altmann et al., 2012; Bitner, 1992; Jaakkola et al., 2017; Johansson & Olhager, 2006; Schmenner, 1986). However, the TaskRabbit case revealed the service contract conclusion can be performed with no physical contact between customer and provider. Moreover, there are platform services that do not even require any physical contact for the entire service process, including contract conclusion, provisioning, and delivery. Examples of these platform services are online services, such as music streaming, video-on-demand online, and cloud services. The lack of research into these is a shortcoming that needs to be addressed.

Second, in existing classification schemes, the degree of customization and the degree of standardization cannot be rated as high at the same time. If one service is rated as highly customized, it cannot be rated as standardized (Fisk et al., 1993; Holmqvist & Grönroos, 2012; Lovelock & Gummesson, 2004; Schmenner, 1986). However, businesses based on platforms, such as TaskRabbit, can provide not only standardized services through the availability of public domain software, the ubiquitous internet, and computing power (Haile & Altmann, 2016a, 2016b) but also highly customized services (e.g., openness and flexibility) through digitalization and automation (Choudary et al., 2016). This point is a shortcoming of the existing classifications.

Third, although interactions between customers and providers have often been discussed (Barnes, Collier, Ponder, & Williams, 2013; Barnes, Ponder, & Hopkins, 2015; Bitner, Booms, & Tetreault, 1990), the environment (virtual or real) in which the interactions occur has received insufficient attention. Existing classifications have the shortcoming of only considering service transactions that can either occur in the real world or in the virtual world. Combinations of occurrences in the real and virtual worlds (e.g., in the case of the platform TaskRabbit service) cannot be expressed.

2.5 Discussion of results: new attribute types for platform services

From the analysis of the TaskRabbit case in Section 2.4, it is clear the attribute types of existing classifications are insufficient for describing platform services. To resolve the three shortcomings identified in Section 2.4, additional attribute types are necessary to describe platform services comprehensively. Three new attribute types are now proposed to add to the classification presented in Table 2.1.

The first new attribute type, which is related to the first shortcoming in Section 2.4, describes the 'degree of involvement' of actors in the service process, covering the quality of interaction and the type of information exchanged. 'Degree of involvement' expresses the quality of interaction with the actors.

Regarding the second shortcoming listed in Section 2.4, if people are familiar with digital devices, they are more likely to join a platform (as in the case of TaskRabbit). Knowing how to use a technical device is a competency (skills and knowledge; Vargo and Lusch, 2004, 2008). Therefore, this new attribute type is called 'degree of competency.' A high 'degree of competency' allows the platform user to use a service more effectively and to obtain a more customized service through the interaction. Consequently, the higher the 'degree of competency,' the higher the 'degree of involvement' can be.

The third new attribute type is 'service scene,' which addresses the third shortcoming. 'Service scene' is defined as a sequence of continuous actions in the service process that can occur in the virtual world or the real world. This definition allows for a combination of occurrences in the virtual world and the real world and helps describe where services are agreed upon, provisioned, and delivered.

These new attributes were derived by studying the similarities and differences between existing service classifications and their attributes. Although this approach has been widely used in previous studies, this one has some distinctiveness. First, this study analyzed various research fields, such as economics, marketing, and innovation, as well as different research foci, such as customer management and service delivery systems, without limitations. Second, the case study and new attributes are presented so they can be applied generally rather than in specific fields, such as organization, marketing, service operation, or innovation. Based on an understanding of existing service classifications, new attributes were proposed to describe new services. New attributes define the characteristics of the change, so existing and new services can be explained together within the industry, and this explanation can be reflected in organizational, institutional, and policy changes that need to be considered together according to the industry changes.

Finally, these new attributes have some important meanings for existing knowledge. First, the new attributes for services help us understand the emerging nature of services. Second, the new attributes demonstrate the need to continue discussing the nature of industries as they are transformed by technology. Third, the understanding of the nature of services that results from these discussions may be reflected in revisions to industry classification tables. For example, one of the industrial classifications describing emerging services is similar to this study's findings. The NAICS, a classification of economic activity in the US, categorizes industries according to their production processes. Each revision describes the characteristics of the sector and explains how those characteristics are reflected in the classification. For example, the description of the characteristics of NAICS 'Sector 51 – Information' includes that the product is intangible or takes any specific form, and that no direct contact between supplier and customer is required during the delivery process (U.S. Census Bureau, 2022). The form of classification varies depending on the purpose and type, but it is necessary to understand the changing characteristics of the industry to classify it.

2.6 Conclusions

This chapter addressed the shortcomings of existing service classifications. A systematic literature review was conducted of existing service classifications and their attributes. Similarities were identified between existing classification schemes regarding customers and managing processes. To identify limitations, existing attributes were applied to the platform service TaskRabbit. Traditional attributes are insufficient to explain the TaskRabbit use case. Therefore, three additional attributes were proposed to cover emerging platform services and a consolidated service scheme.

There are a few limitations to this research. First, there may be articles not included in the analysis. Although a comprehensive methodology was followed to find all relevant studies, only one database, the WoS, was utilized. Second, as analyzing the classification schemes and attributes was conducted based on author's own interpretations, additional quantitative methods using text and clustering analyses might be considered less subjective.

Although there are many service classifications, they fail to explain the current transitions from traditional services to pure online services (e.g., video rental shop to online streaming) caused by technological developments. To understand platform services, an appropriate service classification scheme is necessary.

Chapter 3. Skill Changes Within an Occupation: A Case Study of Cashiers

3.1 Introduction

3.1.1 Research background

Technological change affects labor regardless of the types of jobs, tasks, and levels of skills. Due to the continuing advancement of technology, a huge number of people may experience technological changes in various ways, such as losing their jobs to machines, declining wages. Many theoretical and empirical studies have demonstrated this issue using economic factors, such as education, wage, capital, and productivity. The impact of computerization and automation on jobs have been confirmed by several studies (Acemoglu & Restrepo, 2017; Autor, Levy, & Murnane, 2003; Frey & Osborne, 2017; Goos, Manning, & Salomons, 2014; Michaels, Natraj, & Van Reenen, 2014; Spitz-Oener, 2006) including polarization between skill levels (Acemoglu & Restrepo, 2018b; Dengler & Matthes, 2018; Goos, Manning, & Salomons, 2009; Goos et al., 2014; Michaels et al., 2014; Spitz-Oener, 2006).

To study how technology impacts jobs, the task-based model from Autor et al. (2003) has been used in many studies. This highly useful model can explain the impact of technology on jobs, but it has the limitation that one representative task describes one job. The task-based model treats a task as a discrete activity and does not consider the social and organizational aspects of task complexity, such as how well tasks are connected or the various skills required to perform them (Fernández-Macías & Bisello, 2022). As a result, the task-based model may be assumed that each task can be replaced by a machine. Thus, if a representative type of task (e.g., a routine task) is replaced by technology, then either the job that is represented by the task or the entire workforce that is thought to perform the task is replaced by technology (e.g., Autor et al., 2003; Frey and Osborne, 2017). Furthermore, the education level of the worker performing this task is considered equivalent to the skill level. For example, studies have indicated that skill-biased technological change favors higher-skilled workers (i.e., those with college degrees) over lower-skilled workers, creating a wage gap between education levels (e.g., Frey and Osborne, 2017; Goos and Manning, 2007; Michaels et al., 2014; Spitz-Oener, 2006).

The limitations of the task-based model, in which a single task represents a single occupation, have been discussed and addressed in various studies. Autor (2015) highlights changes in combinations of tasks within an occupation casued by technology. Analyses of the impact of technology have also extended to tasks within occupations (Arntz et al., 2017). These studies have revealed each occupation has a different composition of tasks, and implications can be drawn by examining tasks within occupations. However, few attempts have been made to study the skills required for workers to perform their jobs, to analyze skills as indicators for education, to analyze skills and tasks within occupations, or to study changes in skills and tasks together.

3.1.2 Problem description

It seems obvious that technological changes are unavoidable, and that technology makes differences at work. Technological change is not a one-time event but a continuous process of transformation that induces restructuring in socio-economic systems (Dolata, 2009; Geels, 2002; Geels & Schot, 2007; Perez, 1983, 2010). This restructuring process involves how technology development relates to technology clusters, institutions, social systems, and policies, and how actors in the systems behave in response to innovation (Dolata, 2013, 2018).

As a transformation caused by technology and innovation occurs dynamically, its effects should be perceived as a whole. Technological innovation is not synonymous with technological diffusion, which is why the analysis of social change caused by technological change needs to include policy and economic change processes. The field of technological innovation focuses the direct relationship between technology as a cause and social change as an effect, whereas social change occurs holistically as a result of both direct and indirect effects (Boyd & Holton, 2018). However, previous studies have mostly investigated how technology development affects jobs and analyzed related tasks by assuming a direct relationship between technology and task (Acemoglu & Restrepo, 2018b; Autor et al., 2003; Goos et al., 2014; Michaels et al., 2014; Spitz-Oener, 2006). From the perspective of workers, who are a part of any changes, the question of how workers react to technological changes and their skills has received little attention.

Sets of tasks are occupations, and skills are needed to perform tasks. With technology, tasks within occupations are changing (Arntz et al., 2017; Atalay, Phongthiengtham, Sotelo, & Tannenbaum, 2020; Bittarello, Kramarz, & Maitre, 2018). As part of dynamic transformation, skills within occupations should also change.

Skills are workers' capabilities based on education, training, and experiences (O*NET, 2020a). New technology leads to changes in skills for workers, since a learning process begins when new technology is introduced (Arrow, 1962). Therefore, observing changes in skills can help to determine how workers react and respond to technological changes. Furthermore, by examining the issue from the perspective of workers and skills, the comparative advantages held by workers can be explored, as well as what types of skills are strengthened and weakened to meet tasks affected by technological changes within jobs.

3.1.3 Relevancy

Technological changes occur simultaneously, affecting and relating to all actors. When new technologies are applied, the impact on each sector varies depending on the organization, structure, and institutions of that sector. Dolata (2013) describes this changes as "technology-induced socioeconomic transformation" (p. 28). In Dolata's analytical framework, a new technology can cause varying degrees of change, but it is not the technology that determines the manner or level of change but the organizations, institutions, and actors that embrace and adapt to the new technology (Dolata, 2013, 2018). Therefore, if technology affects tasks and occupations, as discussed in previous studies, changes should be evident in the skills of workers. This assumption that, if there is a change in a task due to the influence of technology, there will also be a change in the related skill, has rarely been studied from the perspective of relating tasks and skills despite changes in tasks and changes in skills due to the impact of technology constantly being discussed individually. Therefore, it is relevant to examine whether changes in tasks and skills are related and interact.

3.1.4 Research objective

The research objective of this chapter is to understand transformation within an occupation by observing changes in skills and tasks. To achieve this objective, the case of cashiers was investigated. Cashiers' role is currently changing, with computerized in-store tools and equipment, such as self-checkout stands, point-of-sale (POS) systems, optical scanners, credit card readers, and payment methods other than cash in retail stores. Nevertheless, many cashiers still exist in the workforce.

The study in this chapter investigated how cashiers have considered and reacted to technological change (i.e., to the computerized in-store tools). Cashier awareness and transformation should be enough to ensure the occupation remains at large. Therefore, a qualitative study on cashier jobs was conducted to investigate the following hypotheses:

H1) The required tasks of cashiers are changed to focus on non-routine tasks, which are difficult to codify and which can be performed better by humans than machines.

H2) The skills of cashiers are changed to focus on interactive, cognitive, and social elements.

Proving or rejecting these hypotheses helps to implement a structural and constructive model for all actors and provides practical support for both innovation and labor. Technological change impacting tasks and skills might be represented as a complex adaptive system. This system can be described as a continuous process of transformation that induces restructuring processes in socio-economic systems.

The remainder of this chapter is organized as follows: Section 3.2 explains the research model, including two hypotheses, for a case study of cashiers. Section 3.3 describes the research methodology, data, and process of data collection. The analysis results are introduced and discussed in Section 3.4. Finally, Section 3.5 concludes the study with a summary of the major findings, contributions, and limitations.

3.2 Research model

The study in this chapter analyzes how an actor responds to technological changes and how the actor is affected by such changes in a socio-economic system. To conduct this examination, an occupation was identified for the qualitative analysis that has been considered at high risk of automation and computerization, has been taken a large number of employments from the overall workforce, and was ordinary and old enough to conduct a long-term analysis.

When cashiers are discussed, cashiers at grocery stores are thought of. Grocery stores have long embraced technology, including POS, card readers, and near-field communication (NFC) contactless payments, which are used face-to-face between cashiers and customers at the checkout counter. In addition, technology enables unmanned stores that do not require a cashier to be present. For example, Amazon announced its first cashierless store, Amazon Go,[5] in 2016. The technological change associated with the cashier includes everything from complementing the cashier's job to possibly replacing the cashier. As discussed in Chapter 2, however, the way service is delivered and the relationship with the customer matter. Cashiers are highly relevant to services in which they are expected to provide specific value, and technology can complement their work to either make it more efficient or to displace cashiers. As such, cashiers are deemed an appropriate case to examine both the changes in tasks and skills due to technological change.

Considering the current situation of cashiers and the conditions necessary for the case study, the occupation is considered highly probable to be substituted by technology in the near future (Frey & Osborne, 2017), and its employment size is large. For instance, there were about 3.6 million cashier jobs in 2018 in U.S. (Bureau of Labor Statistics, 2018). In addition, data for the occupation have been available for a long time. Therefore, the job of cashier was chosen for the case. The case of cashiers is based on the descriptive data of tasks and skills collected from the Occupational Information Network database (O*NET, 2018).

[5] Amazon Go (December 2016) announced ‘introduce Amazon Go and the world's most advanced shopping technology (https://www.youtube.com/watch?v=NrmMk1Myrxc).’

3.2.1 Hypothesis 1, regarding the tasks of cashiers

Previous studies have described changes in technologies as triggering new and more complex tasks within occupations that only humans can perform, even better than machines (Acemoglu & Restrepo, 2018c; Autor, 2015; Autor et al., 2003; Bessen, 2015; Spitz-Oener, 2006). Therefore, the tasks of cashiers should be changed with the adoption of new technology in the working environment. Especially tasks that can be performed by machines and programs, would no longer be significant, but tasks that are difficult to run by automated systems would be strengthened.

Based on this assumption, the first hypothesis is that the tasks of cashiers have been changed to focus on tasks that are difficult to codify. There is expected to be a general tendency toward requiring more cognitive and social tasks, which can be performed better and more efficiently by humans than by machines.

Hypothesis 1: The required tasks of cashiers are changed to focus on non-routine tasks, which are difficult to codify and which can be performed better by humans than machines.

This study reviews tasks based on Spitz-Oener's (2006) criterion of dividing routine and non-routine tasks if the task is defined well enough to codify and to perform by machine. Therefore, routine tasks are identified as those that can be replaced and substituted by machines more easily than non-routine tasks. In addition, non-routine tasks should be related to cognitive and social skills, which greatly depend on the cashier's tacit knowledge and working experiences. Thus, these non-routine tasks are difficult to turn into software programs and technical systems, as their processes are too complicated to be broken down into definitive steps that can be coded with many variables for automation.

If Hypothesis 1 is accepted, it would demonstrate the cashier job has been modified over time; within the occupation, a configuration of tasks has been transformed into performing more non-routine and social tasks than routine tasks.

3.2.2 Hypothesis 2, regarding the skills of cashiers

In addition to changes in tasks, skills should be transformed to utilize non-routine and complex tasks. Skills related to interactive, cognitive, and social elements appear important. These new skills have been mentioned in previous studies as significant for performing complex tasks and are needed to give workers a comparative advantage (Acemoglu & Restrepo, 2018c; Autor, 2015; Bessen, 2015). Therefore, workers focus on acquiring those skills in which they have comparative advantages. Considering the framework of socio-economic transformation, cashiers also attempt to hold various skills to conduct adjusted tasks as actors in the socio-economic system. Therefore, the second hypothesis concerns the transformation of cashier skills over time.

Hypothesis 2: The skills of cashiers are changed to focus on interactive, cognitive, and social elements.

If the two hypotheses are accepted, these demonstrate the tasks and skills of cashiers undergo a continuous dynamic transformation that responds to a changing working environment induced by technological changes. Moreover, instead of observing technological influences on an entire economy or the labor market, this study observed how one actor (the cashier) responds to technological changes in a socio-economic system. With these hypotheses, this study addresses how the job of cashiers will develop in the future through task transformations and how cashiers acknowledge changes in the required skills.

3.3 Methodology and data collection

3.3.1 Methodology

In this thesis, a qualitative case-study approach was conducted using secondary data. Secondary data are collected by official institutions and are useful for studying a long period (Bryman, 2012). Moreover, a case study is advantageous for understanding changes that occur via interconnections of technology, individuals, organizations, society, and policies (Spenner, 1983; Yin, 2014). Therefore, to conduct a case study on cashiers, the Occupational Information Network (O*NET) database was selected. The O*NET is a program that provides occupational information in the US. The database contains standardized information for occupations and updates the data from workers in each occupation.[6] The U.S. Department of Labor, Employment and Training Administration compiled the database based on surveys by the U.S. Department of Labor and its affiliated

[6] National Center for O*NET Development. About O*NET. O*NET Resource Center. Retrieved June 20, 2023, from https://www.onetcenter.org/overview.html

organizations. Questionnaires on tasks are answered by workers, and skills are reviewed and set by experts based on updated information from labor in the field (O*NET, 2020b). All the data are publicly available.

In the database, occupations are described according to their characteristics regarding the knowledge, skills, and abilities used to perform tasks and activities outlined in the O*NET content model. Each occupation is defined by the O*NET Standard Occupational Classification (O*NET-SOC) and profiled using the information from the content model.[7] The content model organizes information about the characteristics of workers and jobs. Information on workers consists largely of worker characteristics, worker requirements, and experience requirements, and information about jobs consists of occupational requirements, workforce characteristics, and occupation-specific information (O*NET, 2020b).

The O*NET is a revised version of the Dictionary of Occupational Titles (Hadden, Kravets, & Muntaner, 2004; Mariani, 1999). The DOT, which was developed in the 1930s to provide descriptive information about all occupations (Peterson et al., 2001), has been used frequently in economic studies on labor and jobs since its formation. The O*NET has been employed in many studies to identify tasks (Autor & Dorn, 2013; Autor et al., 2003; Ross, 2017; Spitz-Oener, 2006), characterize occupations (Frey & Osborne, 2017), and capture social skills in the labor market (Deming, 2017). Furthermore, the O*NET is used to indicate the skill importance related to occupations (Alabdulkareem et al., 2018), to use

---

[7] National Center for O*NET Development. About O*NET. O*NET Resource Center. Retrieved June 20, 2023, from https://www.onetcenter.org/overview.html

the characteristics of occupations to search for alternative occupations (Van Fossen, Chang, Ford, Mack, & R. Cotten, 2022), and to validate a newly constructed research dataset (Atalay et al., 2020). In previous studies, factors suitable for the research purpose have been selected, and necessary data, explanatory data, or scale data were used accordingly. This study also selected variables, tasks, and skills that fit the purpose and research questions of this study and use the related description and scale data as analysis data. Therefore, the O*NET database is suitable for analyzing an occupation's skills and tasks in depth using the qualitative approach presented in this paper. Finally, data on cashiers from 2003 and 2018 (O*NET 5.0 Database of 2003 and O*NET 23.0 Database of 2018) were collected online through the O*NET Resource Center (www.onetcenter.org).

The O*NET database comprises data from 2003 to 2023 (final access to check in June 2023). From 2003 through August 2016, O*NET released data irregularly once or twice a year, and since August 2016, it has released data regularly in February, May, August, and November of each year. The occupations updated in each release are different. For example, the August 2017 data (O*NET 22.0) included '100 occupations updated,' as did the August 2018 data (O*NET 23.0), but the lists of 100 updated occupations differ. The data releases and updates are simultaneous and must contain the same data points. This study also checked for data that do not meet these conditions. For example, data that is released at the same time but updated at different times, and data with different data points could still be analyzed. After several checks of the data in this study, it is concluded that data with all the detailed data points being comparable are appropriate for this study's analysis.

The data about tasks and skills are a few of the available files from 2003 that have been updated regularly regarding the years and occupations. Analyzing this situation with respect to data availability, the data for 2003 and 2018 were chosen. These two datasets are the longest period apart. The 2003 (O*NET 5.0) data are from the first dataset configured by the O*NET program, and the most updated dataset at the time of data collection was from August 2018 (O*NET 23.0). The files for 2003 were retrieved from the O*NET 5.0 database, and the files for 2018 were retrieved from the O*NET 23.0 database.

Moreover, this period of data collection coincided with an economic downturn and with the continuous and rapid change in the technologies thought to affect work. In the 2000s, the discussion of the impact of computerization on work began in earnest (e.g., Autor et al., 2003; Spitz-Oener, 2006); and in the 2010s, the discussion continued with the impact of automation, including the Fourth Industrial Revolution, robotics, and artificial intelligence (e.g., Acemoglu and Restrepo, 2017, 2018a; Cirillo et al., 2021). Moreover, between 2003 and 2018, the financial crisis in the US led to a prolonged general recession (Farber, 2017; Hershbein & Kahn, 2018). At the same time, the rise of platform-based businesses changed how employment and labor are provided (Adams, Freedman, & Prassl, 2018; OECD, 2019). Instability in the labor market due to technological change, economic downturns, and industry changes are mentioned in relation to the period of data collection for the cashier case. An obvious limitation of this study is that it is not possible to prove directly the change in cashiers' tasks and skills due to the introduction of a particular technology. As discussed in previous studies, the limitations of analyzing the impact of technological change as a unidirectional or direct cause-and-effect relationship have long been recognized (Atkinson & Stiglitz, 1969; Boyd & Holton, 2018; Dolata, 2009). Although direct cause and effect is not possible to demonstrate in the case of cashiers, it is nonetheless important to note that this study provides a detailed consideration of how complex socio-economic changes impact an occupation.

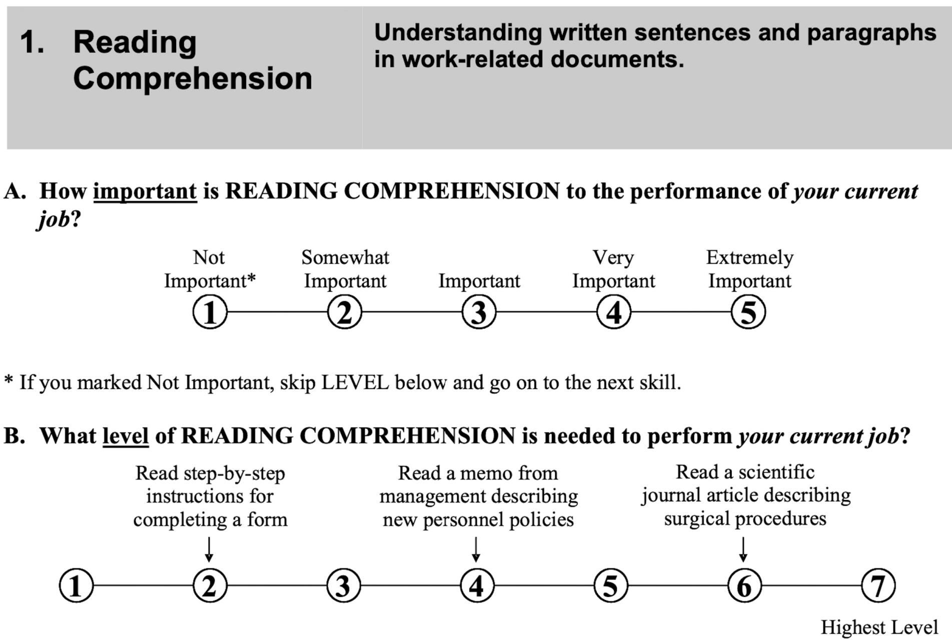
Therefore, this data-collection period is likely to contain significant changes in the tasks and skills of workers due to changes in the labor market caused by the economic downturn, coupled with changes in technology.

3.3.2 Data collection on tasks

The job of a cashier consists of major and minor tasks. All the information related to tasks was collected from the document titled 'Task Statements,' which is attached to each version of the O*NET dataset and is one of the available files for tasks in 2003 and 2018. Within the task statement, the common data points are the O*NET-SOC code, task, date, and source. The data point 'task' provides a list of defined tasks for each occupation coded by the O*NET (O*NET, 2018). Data were collected for all tasks of the cashier between 2003 and 2018. Regarding task changes, task descriptions from the list of defined tasks were used to analyze how a task has changed in detail. The collected tasks are tagged alphabetically (see Appendix Table A), together with task descriptions from the document 'Task Statements'(O*NET, 2018).

3.3.3 Data collection on skills

Information about skills was obtained from a document titled ‘Skills’ that is included in the O*NET dataset for each year, the same as for tasks (O*NET, 2018). The ‘Skills’ document lists elements used for performing the tasks and provides information about the skill name, scales and the data values of skill importance (Scale ID: IM), scaled from 1 to 5, and level of skill (Scale ID: LV), scaled from 0 to 7. Importance and level are two scales that describe skills in O*NET. Figure 3.1 provides an example of a question item (reading comprehension) in the questionnaire and is illustrates how the questions on the two scales of skill are connected (O*NET, 2020a). Since the two types of skill data (IM and LV) are related, it was decided to use them together to analyze the skill.



1. Reading Comprehension	Understanding written sentences and paragraphs in work-related documents.

A. How important is READING COMPREHENSION to the performance of *your current job*?

Not Important* (1) — Somewhat Important (2) — Important (3) — Very Important (4) — Extremely Important (5)

* If you marked Not Important, skip LEVEL below and go on to the next skill.

B. What level of READING COMPREHENSION is needed to perform *your current job*?

(1) — (2) Read step-by-step instructions for completing a form — (3) — (4) Read a memo from management describing new personnel policies — (5) — (6) Read a scientific journal article describing surgical procedures — (7) Highest Level

Figure 3.1 Example of the questionnaire from the O*NET data-collection program

Skills are defined and classified in a document titled ‘Content Model Reference,’ which is included in the annual dataset with other documents. A full list of skills is provided in Appendix Table D, together with a description of each skill. Skills are grouped as classifications in the document as ‘basic skills’ and ‘cross-functional skills.’ Basic skills are defined as the foundation for workers’ capacities and cover learning and acquiring knowledge (O*NET, 2018, 2020b). Cross-functional skills are advanced capacities for performing tasks arising on the job (O*NET, 2018, 2020b). The collected data for 2003 and 2018 were compared regarding the scales of importance and level of skill.

3.4 Data analysis and findings

3.4.1 Analysis results

3.4.1.1 Tasks of cashiers

All the tasks required to perform the cashier job were reviewed for 2003 and 2018. As tasks have changed over time, some descriptions have also been revised and modified regarding contents and expressions. These changes are summarized in Table 3.1. There are tasks that appeared only in one year, or their descriptions differed in each year. If a specific task appeared only in one year, that year’s definition was used to explain the task; otherwise, the description from 2018 was chosen, which was the latest when the described contents were common in both years.

The number of tasks increased in 2018 (29) compared with 2003 (26). One task from 2003 (T1) disappeared in 2018. Three tasks (T4, T18, and T28) were revised for their contents in 2018. All three tasks have developed in detail. For example, T4 covered only 'resolve customers' complaints' in 2003 but became 'assist customers by providing information and resolving their complaints' in 2018. Four tasks (T3, T5, T14, and T29) newly appeared in 2018. In general, these four new tasks are related directly and indirectly to people. In particular, T5 and T14 involved supporting customers at stores. T29 was related to co-workers, and T3 was relevant to both customers and co-workers.

Table 3.1 Cashier tasks and their classification for 2003 and 2018

Year		2003	2018
Task	T1	**Accept reservations or requests for take-out orders.**	
	T2	Answer customers' questions and provide information on procedures or policies.	
	T3		**Answer incoming phone calls.**
	T4	**Resolve customer complaints.**	**Assist customers by providing information and resolving their complaints.**
	T5		**Assist with duties in other areas of the store, such as monitoring fitting rooms or bagging and carrying out customers' items.**
	T6	Bag, box, wrap, or gift-wrap merchandise, and prepare packages for shipment.	
	T7	Calculate total payments received during a time period, and reconcile this with total sales.	
	T8	Cash checks for customers.	
	T9	Compile and maintain non-monetary reports and records.	
	T10	Compute and record totals of transactions.	
	T11	Count money in cash drawers at the beginning of shifts to ensure that amounts are	

	correct and that there is adequate change.	
T12	Establish or identify prices of goods, services, or admission, and tabulate bills, using calculators, cash registers, or optical price scanners.	
T13	Greet customers entering establishments.	
T14		**Help customers find the location of products.**
T15	Issue receipts, refunds, credits, or change due to customers.	
T16	Issue trading stamps and redeem food stamps and coupons.	
T17	Keep periodic balance sheets of amounts and numbers of transactions.	
T18	**Maintain clean and orderly checkout areas.**	**Maintain clean and orderly checkout areas and complete other general cleaning duties, such as mopping floors and emptying trash cans.**
T19	Monitor checkout stations to ensure that they have adequate cash available and that they are staffed appropriately.	
T20	Offer customers carry-out service at the completion of transactions.	
T21	Pay company bills by cash, vouchers, or checks.	
T22	Post charges against guests' or patients' accounts.	
T23	Process merchandise returns and exchanges.	
T24	Receive payment by cash, check, credit cards, vouchers, or automatic debits.	
T25	Request information or assistance using paging systems.	
T26	Sell tickets and other items to customers.	
T27	Sort, count, and wrap currency and coins.	
T28	**Stock shelves, and mark prices on shelves and items.**	**Stock shelves, and mark prices on shelves and items.**
T29		**Supervise others and provide on-the-job training.**
T30	Weigh items sold by weight to determine prices.	

(*Note: The tasks were reorganized by the author based on documents from the O*NET.)

3.4.1.2 Cashier skills

Skills are required to perform tasks at a certain level and importance. Following the changes in the list of tasks, this study examined the skills listed from 2003 and 2018 to understand the changes. The importance and level of skills were compared between the two years.

In Figures 3.2 and 3.3, the x-axis depicts the names of skills, and the y-axis is the scale of the data. All 35 skills on the x-axis are sorted according to the basic skills of the first 10 elements and the cross-functional skills of the remaining 25 elements. Within these two groups, the skills are sorted according to significances in 2003 from highest to lowest. The data points for 2003 are connected with a gray line, although there are no dependencies between the skills. The data points drawn in black triangles denote the values of skills in 2018. The value labels on the x-axis are not identical in the two figures, as the values of skill importance and skill level in 2003 were listed differently from highest to lowest by their values. For instance, a value of skill importance for one skill is high but the value of skill level for the same skill can be low. Since even one skill was greatly important to perform tasks, it would not mean the skill was needed at a high degree to perform them.

Regarding skill importance in Figure 3.2, the data values are based on the answers to 'How important is the skill?' from 1 'not important' to 5 'extremely important.' In 2003, the lowest value obtained was 1, and the highest was 4.16 for the skill mathematics. The remaining skills needed to perform the cashier job were within this range. In 2003, mathematics was the most important skill, which meant it had the highest value, but the most important skill changed to service orientation in 2018.

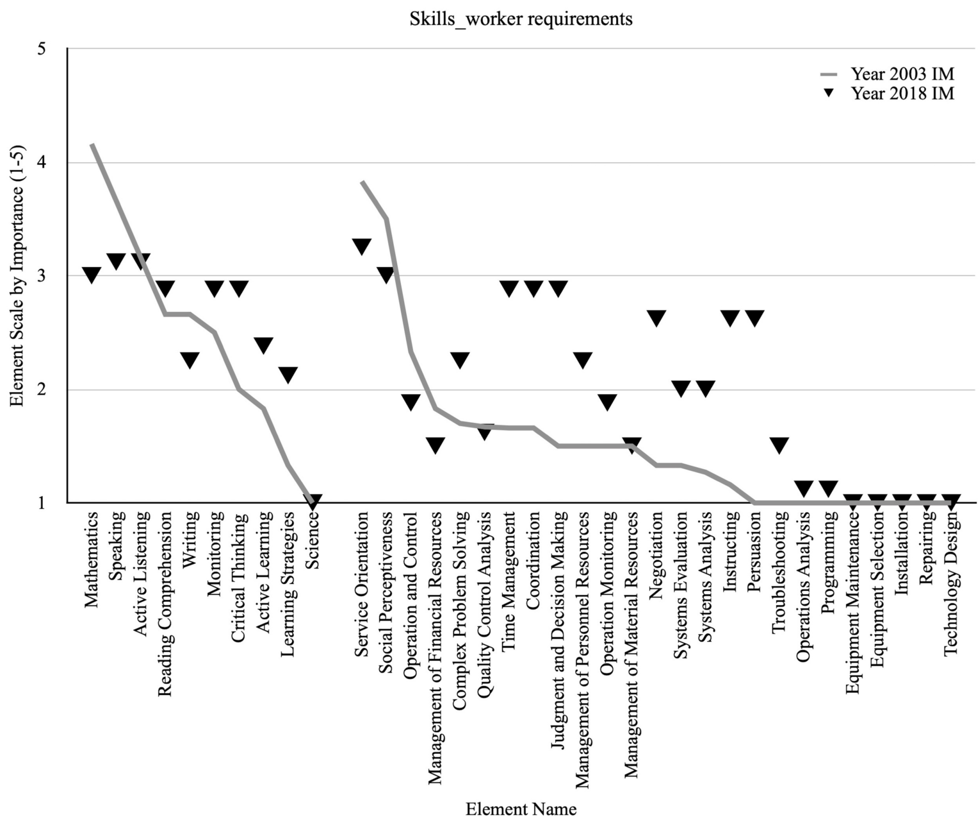


Figure 3.2 Cashier skills by importance

Only two cross-functional skills were considered important at some level in 2003, but the importance of cross-functional skills increased in 2018. Two cross-functional skills (instructing and persuasion) received two times as much attention in 2018 than in 2003. However, the following skills have never been considered important: science, technology design, equipment selection, installation, equipment maintenance, and repairing. Except for to science, the other five all describe technical skills.

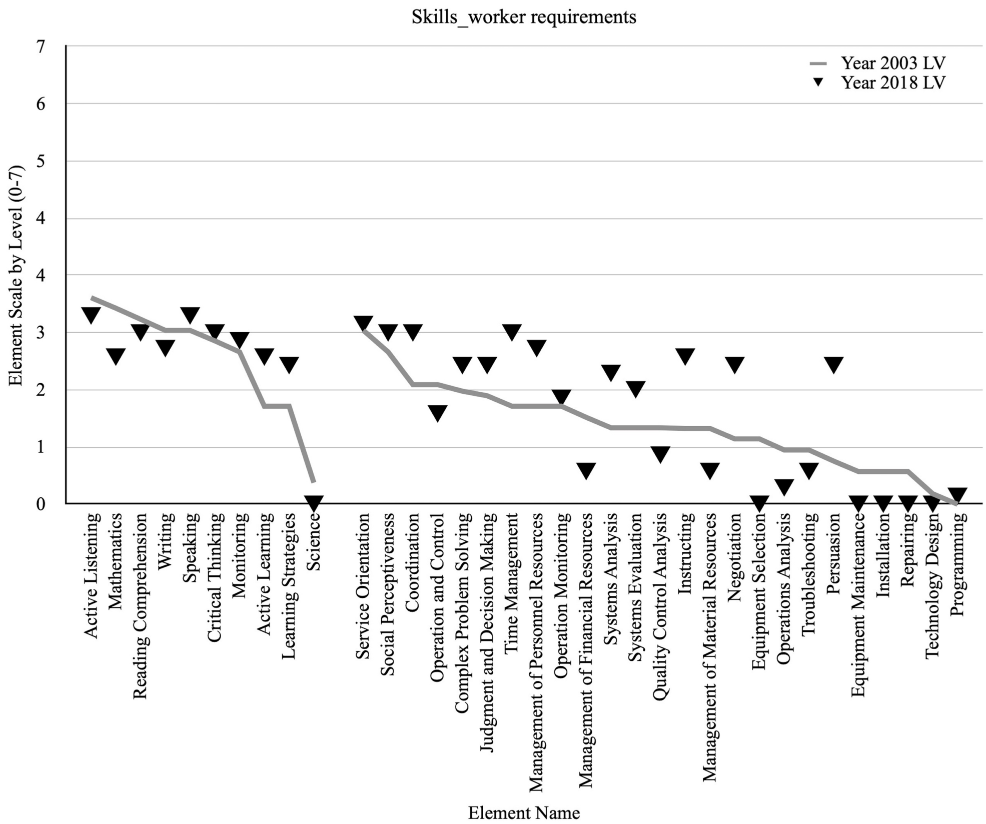


Figure 3.3 Cashier skills by level

Second, regarding skill level, the data values are based on answers to 'What level of the skill is needed?' ranging from 0 to 7. The lowest score (0) meant an answer was related to the first question about the importance of the skill. When a skill was rated as unimportant in answer to the first question, it was not considered for the second question regarding skill level.

Figure 3.3 illustrates that the lowest value obtained was 0, and the highest value was 3.16 in 2003. All the skills needed to perform the cashier job were within this range. The maximum level of skill was 7, but 3.16 was the highest score of the data, indicating that all the skills were needed at middle and low levels. In addition, the basic skills for cashier jobs were necessary at a relatively higher level compared with the cross-functional skills for cashier jobs in 2003 and 2018.

Overall, among the cross-functional skills, social skills received particular attention. To work with people, such as customers and co-workers, social skills were acknowledged and demanded at a higher level in 2018 than in 2003. Technical skills were not considered important at all. Regarding the basic skills, the values of 2018 are higher than for 2003 as a whole. Basic skills (e.g., listening, speaking, reading, and thinking) appeared significantly more important than cross-functional skills (e.g., social perceptiveness, coordination, persuasion, negotiation, and instructing) in terms of skill importance and level. This finding is reasonable, as basic skills provide the foundation for developing workers' capacities.

3.4.2 Results related to the hypotheses

3.4.2.1 Analysis of results for Hypothesis 1

Hypothesis 1 was formulated because the required tasks of cashiers have changed to focus on tasks that are difficult to codify. To address Hypothesis 1, this study focused on changes in the descriptions of tasks. As discussed in Section 3.4.1.1, tasks appeared, disappeared, and were revised in 2018 compared with 2003, meaning the tasks of cashiers have changed. Most important, cashiers were required to perform a wider range of tasks in 2018 than in 2003. Certain tasks were expanded, such as T4, T18, and T28, and others were newly added, such as T3, T5, T14, and T29.

Some tasks were expanded and descriptions adjusted in 2018 (T4, T18, and T28). T4 only involved resolving customer complaints in 2003, but in 2018 it included assisting customers by providing information. T18 focused on maintaining cleanliness and order in the checkout area in 2003, but an additional responsibility to cover broader areas in general by mopping the floor and emptying waste containers was added for 2018. Furthermore, 2018's T28 included activities regarding returned products in addition to 2003's description of 'stock shelves and mark prices on shelves and items.'

New tasks appeared in 2018 (T3, T5, T14, and T29). Three of these tasks describe work interactions: answering phone calls (T3), helping customers (T14), and supervising and providing training (T29). These tasks are directly connected to customers and colleagues, and cashiers were expected to provide answers and react to customer requests and for colleagues they worked together. Finally, T5 involved recognizing when and where cashier assists are necessary.

Similarly, working areas were expanded to be covered by cashiers physically in 2018. In 2003, the location of cashiers was limited mostly to checkout areas. In 2018, expressions such as ‘other areas of the store (T5)’ appeared, as well as tasks that cannot be performed without moving from checkout stations, such as supervising others, mopping floors, or assisting customers to find products. Moreover, cashiers’ appropriate responses to circumstances were demanded more than before in the new tasks. Typically, working procedures ought to be provided, but these tasks involve the cashier’s continuous recognition of situations and problems.

Consequently, all these tasks are too complicated to be performed by automated systems, as they require cognitive, interactive, and social elements. These elements depend on the cashier’s tacit knowledge and working experiences; for example, cognitive tasks include decision-making and problem-solving processes, as well as interactive and social skills related to society and the organization.

Hypothesis 1 was confirmed by finding a certain tendency toward more non-routine tasks in 2018 than in 2003, and more tasks that are difficult to codify became significant within the job of cashier. Accordingly, the required tasks of cashiers changed to focus on cognitive and social tasks; moreover, although they are not cognitive and social tasks, most of the significant tasks are difficult to codify as non-routine manual tasks in 2018.

3.4.2.2 Analysis of results for Hypothesis 2

In addition to changes in tasks, changes in skills should be considered, especially in areas in which workers perform better than automated systems. For instance, the newly added tasks, such as answering phone calls, helping customers through stores, and supervising, all involve social and interactive elements and require responses to various working conditions. To perform these increased non-routine tasks, cashiers ought to consider skills differently in 2018 than in 2003. Therefore, Hypothesis 2 stated the skills of cashiers have changed to focus on interactive, cognitive, and social elements. To address the second hypothesis, skills were examined for 2003 and 2018, and the detailed characteristics of skills are discussed.

First, skills were ranked differently according to their importance and level. Regarding skill importance and skill level, one skill was highly important, that does not necessarily mean the skill was required at a high level. Some skills were used at high level, whereas other skills could be important because they are used frequently at low level. Regarding skill importance, the most important skill changed from mathematics in 2003 to service orientation in 2018. Regarding skill level, active listening had the highest level in 2003, but this changed to active listening and speaking in 2018.

To compare the changes in skill elements by considering importance and level at the same time, the values of importance and level were added up. In Figure 3.4, the skill differences between 2018 and 2003 are on the y-axis, and the x-axis is the sum of importance and level in cashier skill for 2018. Thus, the figure presents the skill statuses of 2018 with their changes. For instance, persuasion and mathematics are on the right side of the figure, meaning both were considered at similar degrees in 2018. Although the two skills reached the same point for different reasons, persuasion was valued highly in 2018, so it became significant with positive changes, whereas mathematics was valued much less in 2018, so it was positioned with negative changes.

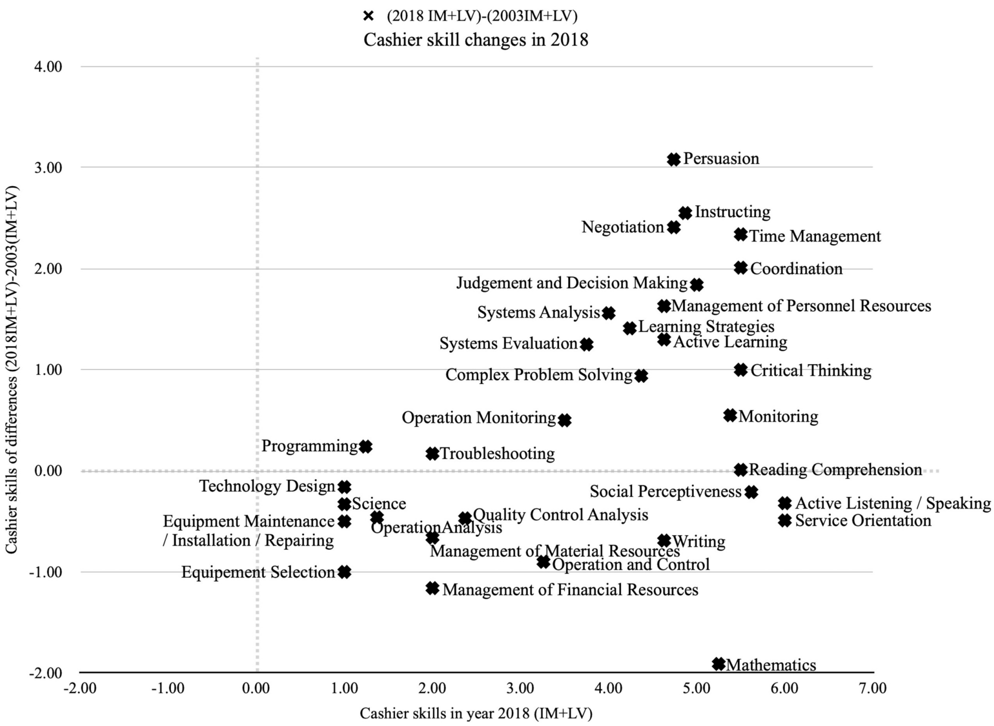


Figure 3.4 Changes to cashier skills in 2018

In Figure 3.4, the first five skills displayed positive skill changes in 2018: persuasion, instructing, negotiation, time management, and coordination. Four skills are used in relating with other people: convincing, changing other's behavior or mind (persuasion), making agreements from differences (negotiation), guiding others (instructing), and organizing different roles and opinions to work together (coordination). Finally, time management is a skill involving managing one's own and other's time. All five skills involve communication and relationships with others.

Three skills on the right side of Figure 3.4 displayed high skill significance in 2018, but their changes are decreasing: active listening, speaking, and service orientation. This positioning reveals they have been considered significant since 2003. Active listening and speaking are basic skills utilized in making conversation at work, and service orientation is more about being ready to help others. Skills for communication were major since 2003, and cashiers mentioned how advanced skills became more important in 2018 for interacting, such as persuasion, instruction, and negotiation. These social skills are difficult to build without the basic skills of listening, talking, and paying attention to others. Technology development has not yet been able to automate these skills.

Regarding interactive and social elements, in 2003 only a few basic skills were considered in communications and relationships, but in 2018 more advanced social skills were required for the job of cashier. Cashiers needed to develop basic skills to improve their skills further in 2018. Regarding the results about changes in tasks, some tasks transformed to more non-routine types of working with people and covering a wider range of working areas.

Mainly focusing on changes, skills can be discussed skills that received more attention in 2018. A group of skills that displayed increases in 2018 involved interactive and social elements. The following skills were related to improving performances and resolving problems.

In Figure 3.4, there is a different group of skills immediately below the first five elements (persuasion, instructing, negotiation, time management, and coordination). This group contains judgment and decision-making, management of personnel resources, system analysis, learning strategies, active learning, systems evaluation, and critical thinking. These skills are on the right side of the figure, with relatively high significance in 2018, but their changes were less than those of the first five skills. These skills were identified and used by cashiers to understand information and choose methods to learn (active learning and learning strategies), to find reasonable solutions to problems (critical thinking), to select and decide proper means and methods at work (judgment and decision-making, systems analysis, and systems evaluation), and to manage staff at work (management of personnel resources).

Changes in skills were observed between the two years. In 2018, skills became more focused on only those elements relevant to cashiers, such as interactive, cognitive, and social elements. Social skills especially received greater attention, as the trend of required tasks moved toward those that could not be performed easily by computers and machines. Social skills are required to work with customers and co-workers in terms of communication and interpersonal relationships. Furthermore, basic skills that relate to improving cross-functional skills generally remained at a moderately higher level than other skills.

Therefore, Hypothesis 2 is confirmed, as the skills of cashiers changed to focus on interactive, social, and cognitive elements. Skills in which workers have a comparative advantage were recognized more by cashiers.

3.4.3 Discussion of results

This study considered the technological changes that occur dynamically and continuously through the interplay between all relevant actors in socio-economic systems (Dolata, 2013, 2018; Perez, 2010) and focused on what has happened within an occupation, cashier. Analyzing the case of cashiers revealed the required tasks have changed steadily, and the skills needed have altered over time.

Previous studies have raised the point that the possibilities of technological changes may trigger new and more complex tasks that can be performed better by humans within occupations (Acemoglu & Restrepo, 2018c; Autor, 2015; Bessen, 2015; Spitz-Oener, 2006). This study confirmed that tasks that are difficult to codify, such as helping customers by managing their requests and providing job training, have tended to become more important in the case of cashiers. The changes regarding the job role emphasize cognitive and social tasks. The most important insight obtained is that changes in the occupation tend toward skills in which workers hold a comparative advantage. Not only did the composition of tasks within the job of cashier change, but major tasks also involved interactive and social elements that were complicated or too expensive to be automated for now. With the changes in tasks, different skills were found to be more important and required at other levels than previously. Cashiers responded to changes by emphasizing relevant skills (i.e., social skills) and reducing less useful skills (i.e., technical skills) for the job. Although it could not be determined whether cashiers' responses were made actively or passively to the transformation revealed in this study, the results indicate that people involved in the job were aware of the changes in their work and chose to develop and improve their advantages.

Atkinson and Stiglitz (1969) argue that technological innovation does not lead to improvements in all factors of production as a whole. Even if one task is automated, it does not matter whether the other tasks are also automated (Atkinson & Stiglitz, 1969). Therefore, although it is important to understand human worker's skills in terms of related factors in socio-economic systems, the challenge is to capture this interaction in a model. This process can begin with this case study of the cashier by examining tasks and skill change simultaneously.

When new technologies are applied, the impact on each sector varies depending on the organization, structure, and institutions of that sector. Dolata (2013) describes this process as "technology-induced socioeconomic transformation" (p. 28). In Dolata's analytical framework, a new technology can cause varying degrees of change, but the technology does not determine the manner or level of change; it is the organizations, institutions, and actors that embrace and adapt to the new technology. These two concepts—the new technology and how it is accepted by the sector— work together to transform.

Therefore, in the case study of cashiers, the changes in the labor environment due to the application of technology (the behavior of an agent offering technological innovation in Figure 3.5) were analyzed and the changes in the tasks and skills of the cashier as an actor (the behavior of an agent offering skills and an agent offering task in Figure 3.5) were examined. The application of technology and the tasks and skills of cashiers have been changing interactively (interrelations between agents in Figure 3.5); as a result, there was a change in emphasis of the tasks and skills that require human interaction and communication between 2003 and 2018. As such, the changes experienced by cashiers as actors in the sector may eventually be linked to the degree of transformation in the sector (affecting behavior and emerging behavior in Figure 3.5). In the end, these interrelated changes involved to the restructuring process in the labor market.

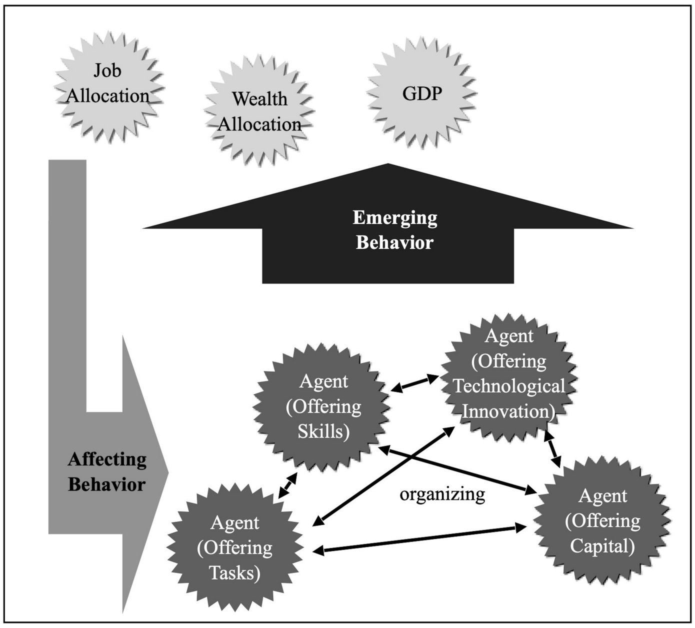


Figure 3.5 Example of a socio-economic system

3.5 Conclusions

3.5.1 Summary of major results

To understand the transformation of jobs by observing changes in skills and tasks at the individual level, the occupation of cashier was analyzed in this study (Rows 1 and 2 of Table 3.2). Descriptive data were used to explore how tasks and skills have transformed together due to technological changes over time. In general, a certain tendency was identified to develop tasks and skills that focused on activities difficult to codify. These tasks and skills involved communication and interpersonal features too implicit to write into software and hardware or that were still expensive to operate by machines (Row 3 of Table 3.2).

Table 3.2 Summary of findings

	Data	Result analysis	Results presentation	Major finding
Section 3.4.1.1	Changes in cashier tasks	Examining how tasks changed over time in one occupation	By task and their descriptions	- The number of tasks has increased in 2018. - Tasks that expanded in detail in 2018 needed to cover a wider scope. - Tasks that newly appeared in 2018 are related to people both directly and indirectly.
Section 3.4.1.2	Changes of importance and level in skill of cashier	Examining how skill changed over time in one occupation	By skill importance (1–5) and skill level (0–7)	- Regarding skill importance, the most important skill changed from mathematics in 2003 to service orientation in 2018. - Regarding skill level, active listening was considered the highest level in 2003, whereas two skills—active listening and speaking—were considered the highest in 2018. - Instructing and persuasion appeared to have increased in level and importance in 2018.

Section 3.4.1.3 ~ Section 3.4.1.4	Discussing the hypotheses and findings: **changes of skills and tasks in one occupation** - Tasks and skills have transformed together. - Changed tasks and skills involved communication and interpersonal features, which were too implicit to write into software and hardware or could be still too expensive to operate by machines. Chapter 3 revealed that both skills and tasks are changed together in one occupation.
Chapter 4	**Extending the understanding of skills** - Chapter 4 is focused on skills in and across occupations. - Chapter 4 proposes a framework to capture skill changes and express how skills account for salary and productivity.

3.5.2 Contributions

The theoretical background of this study is based on the framework of technology-induced transformation (Dolata, 2009, 2013) from innovation studies. This study attempts to reveal the significance of extending the current view of technological changes in jobs and workers. Finally, technology development should not be limited to a one-sided effect. Transformations also occur in occupations to respond to external changes. This conclusion may contribute to recent studies on this issue of technological impacts and jobs in various research areas with different perspectives, such as focusing on relations between humans and machines (Sanders, Kaplan, Koch, Schwartz, & Hancock, 2019; Tatasciore, Bowden, Visser, Michailovs, & Loft, 2020) and human reactions toward future technological changes (Skrbiš & Laughland-Booÿ, 2019).

In addition, the case study demonstrated that a qualitative approach using descriptive data can be beneficial and meaningful to complete aggregate levels of economic research as a method of revealing details that used to be missed and could not be confirmed with statistical approaches. Concentrating on one middle-skill occupation was giving an opportunity to understand the changes that occurred within it in depth. Based on this study, other middle-skill occupations can be investigated to search for a general tendency toward changes in tasks and skills. Moreover, other cases regarding skill levels, such as low-skill and high-skill jobs, will make it possible to determine sets of tasks and skills used differently in various occupations.

3.5.3 Limitations

The first limitation of this study is that, by assuming technological changes underlie overall working environments, the study did not show any direct causal relationship between technology and work. No attempt was made to prove any direct causality between technological changes and cashiers. Although technology impacts have been discussed and analyzed extensively in the literature, this study contributed to the existing discussions by enriching them. The second limitation concerns how cognitive tasks were considered in this study. Cognitive characteristics can be considered difficult to discuss regarding specific occupations, meaning perhaps this study dealt with them too broadly. However, tasks in middle-skill jobs can display cognitive characteristics even at a lower level. When cognitive tasks are involved, a cashier's decision-making surely differs from an astronaut's;

however, both are still making decisions to solve issues at work; they are just different, and, as demonstrated in this study, all occupations variously consist of routine, non-routine, manual, and non-manual tasks.

Chapter 4. Skill Significance as a Predictor of How Technology Advancement Impacts Labor, Salary, and Productivity

4.1 Introduction

4.1.1 Research background

Task changes caused by technology in occupations have been discussed in many studies (Acemoglu & Restrepo, 2018b; Arntz et al., 2017; Atalay et al., 2020; Autor et al., 2003; Frey & Osborne, 2017; Spitz-Oener, 2006). Autor, Levy, and Murnane's (2003) task-based model is a well-known framework, explaining and measuring changes in jobs directly. In the task-based model, non-routine analytic tasks are defined by tasks that include mathematics. Non-routine interactive tasks are defined by tasks comprising the directing, controlling, and planning of activities. Routine manual tasks are defined by tasks requiring a certain dexterity, such as finger dexterity (Autor et al., 2003, p. 1323). In the task-based model, routine tasks can be substituted by technology more easily than non-routine tasks. Consequently, workers who mostly perform routine tasks are highly likely to be replaced by machines. By assuming a direct relationship between tasks and technologies, the task-based model provides an explanation for changes in occupation (Autor et al., 2003). Later studies have adopted this task-based model by extending the definitions of tasks (Spitz-Oener, 2006) and reflecting on advanced technologies (Frey & Osborne, 2017).

Studies have also reasonably demonstrated that occupations (i.e., compositions of tasks) and their tasks change, are substituted, and are complemented by technology. Frey and Osborn (2017) claim that technological breakthroughs can make tasks redundant that previously could not be automated and were not substitutable.

As technological advancements cause the substitution of routine tasks, workers need to adapt their skills to perform tasks. Skills are defined here as the capabilities or abilities of workers to perform tasks (Acemoglu & Restrepo, 2018b; Atalay et al., 2020; Autor et al., 2003).

4.1.2 Problem description

In the literature, skills are mostly explained by the level of education of the worker (Autor et al., 2003; Frey & Osborne, 2017; Spitz-Oener, 2006). The level of education is a convenient way to estimate the skills of workers. To quantify this level, data on school enrollment, costs and expenses for education and training, and income through education have been used to measure human capital (Abraham & Mallatt, 2022). However, these factors related to education level do not reflect differences between workers, which are caused by experiences of learning, quality of education (Deming, 2022), or knowing skills that are difficult to certify through formal education. For example, studies have concluded that workers will keep their jobs if human labor holds a comparative advantage, such as interactive skills, social skills, and skills for creative tasks (Autor, 2015, 2022; Frey & Osborne, 2017). However, formal education does not certify these competencies, and the formal education level cannot capture these skills. Despite this issue, only the formal educational level has been considered when analyzing the impact of technological advancement. Changes in skills, except for upgrading through formal education and training, have not been studied much with respect to technological changes. Thus, there is a research gap regarding whether workers employ the same sets of skills or require the same competencies to complete a task as before the task change.

4.1.3 Relevancy

The literature states that occupations with routine cognitive, routine manual, and non-routine manual tasks are performed by workers with a low formal-education level, and occupations requiring analytical interactive tasks are performed by workers with a high formal-education level (Autor et al., 2003; Spitz-Oener, 2006). For instance, Spitz-Oener (2006) found that tasks in occupations are changing toward more analytical and interactive activities, leading to demands for workers with high education who they are believed to perform non-routine cognitive tasks better that workers with low education (Spitz-Oener, 2006). Similarly, Frey and Osborn (2017) measured skills using formal educational levels and claim that high-skilled workers who perform creative and intelligent tasks in the fields of engineering and science are at lower risk of losing their jobs than low-skilled workers. The researchers conclude that workers with a high formal-education level will be highly in demand in the future and will be part of the workforce despite the impact of technological changes (Frey & Osborne, 2017; Goos et al., 2014; Michaels et al., 2014; Spitz-Oener, 2006).

Only a few studies have investigated skills beyond formal education, despite the literature emphasizing the importance of creative tasks (Frey & Osborne, 2017) and non-routine tasks. These tasks require interactive communication skills, and resilience (Autor, 2015). One notable study is that of Deming (2017), which focuses on social skills, especially working with others. The study states that workers with high social skills have an advantage, as they can coordinate tasks at lower costs and work more efficiently with others than workers with low social skills (Deming, 2017). The study found that social skills are highly related to increasing the number of people in certain occupations that require interpersonal skills, and that social skills can be a significant predictor of employment and wages (Deming, 2017). Recently, skills have also been studied to determine the changes in skill requirements and to identify common skills between occupations (Alabdulkareem et al., 2018; Van Fossen et al., 2022).

There is a gap in the existing research. Therefore, it should be investigated whether workers apply the same sets of skills or require the same competencies to complete a task as before the task change and how this situation relates to formal education.

4.1.4 Research objective

When occupations requiring work are transformed, the skills workers use to perform the transformed tasks of those occupations can be expected to be different as well. The objective of this study is to investigate skills regarding their changes across several occupations. Following this research objective, three research questions were formulated for the study in this chapter:

RQ1) How have skills, which are required for performing occupations, changed over time within groups of occupations?

RQ2) How can skill-element significance be used and skill elements be aggregated to simplify their use?

RQ3) How can skill-element significance be used to predict how technological advancement impacts salary and productivity?

To answer the research questions, a case study of skills was conducted. Changes in skills can be observed by checking changes in skill elements. To observe these changes in skills over time, a case-study method was adopted as it is a useful method for answering questions about how or why and to understand present events, especially those that cannot be controlled (Yin, 2014).

The remainder of this chapter is organized as follows: Section 4.2 provides an overview of existing research directions in previous studies on skills. Section 4.3 describes the research methodology and data for a case study of skills. In Section 4.4, skill changes are analyzed and discussed. Based on the analysis results, a framework is proposed to express skills that account for salary and productivity in Sections 4.5 and 4.6. Finally, Section 4.7 concludes the study with a summary of the major findings, contributions, and limitations.

4.2 Existing research directions regarding skills

As identified in the previous chapter, by Deming (2017), Alabdulkareem et al. (2018), and Van Fossen et al. (2022) are the few existing studies on skills. These studies, which regard skills as a worker's abilities to perform a job, focus on social skills and non-routine tasks (Deming, 2017), skills and their complementarities (Alabdulkareem et al., 2018) and skills and job transitions (Van Fossen et al., 2022).

All three studies used the O*NET database (2018) in combination with different national statistical data or survey data. They also used different methods for analyzing their data, including descriptive analysis, regressions, and social network analysis. Deming (2017) used two datasets titled NLSY79 and NLSY97, from the U.S. National Longitudinal Survey of Youth and examined the increasing importance of social skills and non-routine work on wages employing regressions. Alabdulkareem et al. (2018) used data from the Current Population Survey (CPS), which has been produced by the U.S. Census Bureau and the Bureau of Labor Statistics. The CPS identified occupational changes by analyzing answers of survey participants at an interval of 1.5 years. Alabdulkareem et al. (2018) selected those participants who indicated having different occupations in the two surveys and, based on that, built a dataset for US workers' occupational changes between 2014 and 2015 and a social network analysis graph for skill complementarities. Van Fossen et al. (2022) used descriptive statistics and collected data from a survey of 202 truck drivers, in addition to the O*NET database. The survey helped to identify skill similarities for potential transitions to other occupations that truck drivers can be satisfied with once selfdriving trucks emerge.

Regarding the authors' contributions, Deming (2017) can be considered the first major discussion about social skills. The study employed a productivity model that considered human capital as an input factor of productivity to perform a statistical analysis. Social skills, which comprise coordination, negotiation, persuasion, and social perceptiveness from the O*NET, were the focus in the study. Deming (2017) believes social skills contribute to reducing costs when working with others in a team. The analysis results indicate that social skills are negatively correlated with routine tasks, and that social skills are positively related to wages (Deming, 2017). Overall, the study revealed the possibility of using social skills as a predictor of employment and wages.

Alabdulkareem et al. (2018) highlight the importance of skills and an individual worker's ability to adapt their skills. Skills in an occupation are used to calculate the revealed comparative advantage (RCA), which determines the comparative advantage of an occupation compared with another. The result of the analysis is a skill network that the authors employ to explain polarization and related dynamics, such as job transitions, changes in skill requirements due to changes in occupations, and important skills in cities (Alabdulkareem et al., 2018).

The focus of the study by Van Fossen et al. (2022) is identifying alternative occupations for long-distance truck drivers, who are considered at risk of displacement through the emergence of autonomous vehicles. The researchers sought alternative jobs by comparing similarities between occupations. Truck drivers' occupational characteristics, such as knowledge, skills, abilities, vocational interests, and work values, were compared with those of other occupations. In addition, drivers' perceptions about alternative jobs were determined by analyzing data collected through a survey. As a result of examining similarities between truck-driving and other occupations, together with drivers' perceptions and possible transitions, the authors identified optimal alternatives to truck-driving (Van Fossen et al., 2022).

Table 4.1 Comparison of existing research regarding its perspective on skills

	Deming (2017)	**Alabdulkareem et al. (2018)**	**Van Fossen et al. (2022)**
Focus of the Study	Social skills, non-routine tasks	Skills, polarization	Skills, job displacement
Data Used	O*NET and US statistical dataset of NLSY	O*NET and US statistical data of CPS	O*NET and survey data of truck drivers
Method Applied	Regression	Social network analysis	Descriptive statistics
Measure Applied	Costs of trading tasks between workers	Skill complementarity	Skill similarities
Contribution of the Study	Identified social skills are a predictor of wage and employment numbers	Explained skill polarization, job transition, and mobility	Analyzed skills for job transitions and alternative occupations to truck-driving

Despite their substantial contributions, the three studies summarized in Table 4.1 do not analyze how the skills required in occupations have changed over time, nor do they identify the skills that have become more significant in occupations over time. This information would help clarify how tasks (or even occupations) need different types of skills or different levels of skills, or that there is a different importance assigned to skills as the working environment changes over time. Skills are expected to differ over time. To fill this research gap, it is formulated that research question RQ1: How have skills, which are required for performing the tasks of an occupation, changed over time within groups of occupations?

No conceptual model can represent these many skill changes simply. This research gap can be addressed with RQ2: How can skill-element significance be used and skill elements be aggregated to simplify their use?

Moreover, such a conceptual model would help to make more accurate predictions than are currently available. The model would help workers adapt their skills to future demand and help employers select educational services to aid employees transition into successfully completing new tasks. This research gap can be addressed by RQ3: How can skill-element significance be used to predict how technological advancement impacts salary and productivity?

4.3 Methodology

4.3.1 Data description

Data were obtained from the database of the Occupational Information Network (O*NET) of the U.S. Department of Labor, Employment, and Training Administration. The database is based on surveys (O*NET, 2018). This database was known as the DOT until 1998. In 1998, the O*NET replaced the DOT, with a significant change in the database structure (Hadden et al., 2004; Mariani, 1999). This database has been used to study labor and jobs since it was created by the DOT. The O*NET has been applied in many studies to identify tasks (Autor & Dorn, 2013; Autor et al., 2003; Ross, 2017; Spitz-Oener, 2006), characterize occupations (Frey & Osborne, 2017), and describe social skills (Deming, 2017). Furthermore, the O*NET has been used to indicate the skill importance related to occupations (Alabdulkareem et al., 2018), to search for alternative occupations using the characteristics of occupations (Van Fossen et al., 2022), and to validate a newly constructed research dataset (Atalay et al., 2020). Previous studies have selected factors that are appropriate for the research purpose and used the necessary data, descriptive data, or scale data accordingly. In this present study, variables, tasks, and skills that fit the purpose and research questions are also required, and related descriptive data and scale data are used as analysis data. Therefore, the O*NET database is a suitable source for analyzing skills across occupations in depth through the qualitative approach presented in this paper.

The database provides various data on occupations that have been collected regularly over several years in a specific structure, and all the data are publicly available. Since there have also been some updates to the database over the years, the information in some files has changed for certain years, making it difficult to find data that can be compared. The database includes data on ability, education, training, experience, interests, job zones, knowledge, skills, tasks, work activity, work context, work styles, and work values. In addition, references are assigned to files, providing information about the dataset, such as job zone, scales, survey booklet location, and content model (O*NET, 2018). Overall, the O*NET is suitable for analyzing the skills of occupations in this study. Moreover, the O*NET's data provides the opportunity to find perspectives different from previous studies using the same database (Bryman, 2012).

Thirty-five skill elements categorized into seven skill categories are defined in the O*NET database. Skills are the abilities needed to perform tasks and are possible to learn either through formal education and training or through experience The O*NET's categories of occupations are referred to as 'job zones.' The database classifies occupations into five categories, according to the required degrees of working experience, training, and formal education (Appendix C). This information is also used in the analysis (Column 2 of Table 4.2).

4.3.2 Methodology and data collection

Changes in skills can be observed by checking changes in skill elements. To observe these changes in skills over time, a case-study method was used. The case study is a useful method for answering questions about how or why and to understand present events in real life that cannot be controlled (Yin, 2014). To observe changes in skills over time, information about skills from different years should be considered. Data related to skills are collected from the O*NET, and data period is determined based on data availability.

The O*NET contains data from 2003 through 2023 (final access to check in June 2023). In the meantime, data release has been made once or twice a year from 2003 to August 2016, and from August 2016, it has been made regularly in February, May, August, and November every year. The details updated for each released dataset are different. For example, the August 2017 data (O*NET 22.0) announced that it had updated 100 occupations and the August 2018 data (O*NET 23.0) also announced that it had updated 100 occupations. However, the updated 100 occupations for these two years differ. Therefore, in order to look at changes over time in skills for the same occupations in this study, data releases and updates must occur simultaneously and have the same data points. This study also verified that data releases, data updates, and data points do not meet these conditions can still be analyzed for the purpose of this study. For example, it is checked whether data released at the same time but updated at different times were comparable, and whether data points differing in data could be analyzed. After checking the data several times before the analysis of this study, it is concluded that data with all detailed data points comparable are suitable.

The data about skills are in one of available files from 2003 that has been updated regularly regarding the years and occupations. Considering this situation with respect to data availability, which the data releases and updates are simultaneous and must have the same data points, the data for 2003 and 2018 were chosen. These two datasets are the longest periods apart. The 2003 (O*NET 5.0) dataset is the first configured by the O*NET program, and the most updated dataset at the time of data collection was from August 2018 (O*NET 23.0). Therefore, the files for 2003 were retrieved from the O*NET 5.0 database, and the files for 2018 were retrieved from the O*NET 23.0 database (http://www.onetcenter.org; Step [a] of Figure 4.1).

Moreover, this period of data collection coincided with constant and rapid technological change and economic downturn that could affect work. In the 2000s, the discussion on the impact of computerization on employment and wages began increasing (Autor et al., 2003; Spitz-Oener, 2006), and the discussion continued in the 2010s with the development of technology, the Fourth Industrial Revolution, automation including robotics, and artificial intelligence have led to their impact to work (Acemoglu & Restrepo, 2017, 2018a; Cirillo et al., 2021). Moreover, between 2003 and 2018, the US financial crisis prolonged the overall economic downturn (Farber, 2017; Hershbein & Kahn, 2018). At a time when automation and economic downturn can precariously create employment, the rise of platform-based businesses has also changed employment practices (Adams et al., 2018; OECD, 2019). Therefore, this data collection period is likely to have coincided with significant changes in the tasks and skills of workers due to changes in the labor market caused by the economic downturn, coupled with changes in technology.

In the database, occupations are described according to their characteristics regarding the knowledge, skills, and abilities used to perform tasks and activities according to the

O*NET content model. Each occupation is defined by O*NET-SOC and profiled using the information from the content model.[8] The content model organizes information about the characteristics of workers and jobs. Information on workers consists largely of worker characteristics, worker requirements, and experience requirements, and information about jobs consists of occupational requirements, workforce characteristics, and occupation-specific information (O*NET, 2020b).

The files used 'Content Model Reference', which provides definitions of skills, 'Skills', which includes numerical values obtained from surveys for skill importance and skill level, as well as the file 'Questionnaire', which contains the questionnaire about skills. The 'Questionnaire' document contains answers to two questions: 'How important is the skill to the performance of your current job?' and 'What level of skill is needed to perform your current job?' (O*NET, 2020a). The answers are in the form of numbers indicating the degree of skill importance and the required skill level. For the first question regarding skill importance (IM), the answer scale is from 1 to 5. For the second question about the skill level (LV), the scale ranges from 0 to 7. Two scales that describe skills in the O*NET and they are obtained from two connected questions about skills in the questionnaire (see Figure 3.1; O*NET, 2020a). Therefore, since the two types of skill data (IM and LV) are related, it was decided to use them together to analyze the skill.

Regarding using secondary data, which means the researcher of this study was not involved in its collection (Bryman, 2012), An example of the data available for 2018 is in

[8] National Center for O*NET Development. About O*NET. O*NET Resource Center. Retrieved June 20, 2023, from https://www.onetcenter.org/overview.html

Appendix A, and for 2003 it is in Appendix B. Examining the data in the files for the two years revealed a different number of data points per skill element for each year. There are seven data points in 2003 (Appendix B) and 15 data points in 2018 (Appendix A). The seven data points from 2003 are also in 2018 (Appendix B), comprising the Standard Occupational Classification (SOC) code (*O*NET-SOC code*), skill element ID (*element ID*), skill element name (*skill element*), *scale ID* (containing the values of *LV* or *IM*), data value for the scale ID (*data value*), date of data collection (*date*), and source of the data (*source*; Step [b] of Figure 4.1).

A closer examination of the data in the two datasets for 2003 and 2018 revealed the data of the data points for *date* and *source* vary for different occupations. To make the analysis precise, the only occupations considered for the analysis are those that display the survey-taken-date[9] of 2002 in the 2003 O*NET database and the survey-taken-date of 2018 in the 2018 O*NET database. This criterion resulted in about 100 occupations. Furthermore, only the data points that display the exact same SOC code were used (as in the 2018 O*NET database, SOC codes were adjusted, i.e., SOC codes disappeared, SOC codes were added, or SOC codes were merged). These selection criteria meant 37 occupations out of 902 in 2003 and 967 in 2018 were used for the analysis (Step [c] of Figure 4.1). These occupations are listed in Table 4.2, with job zone number, job zone name, and titles of occupations. Of these 37 occupations, two belong to Job Zone 1, 13 belong to Job Zone 2, three belong to

[9] Note: The O*NET does not explicitly state the meaning of the date entered in the database. However, considering the date and the data values for the scale ID changes, it was concluded the date represents when the survey was taken.

Job Zone 3, 12 belong to Job Zone 4, and seven belong to Job Zone 5.

Table 4.2 Occupations that qualify for further analysis are grouped in job zones of the O*NET

Job Zone Number	Job Zone Name and Description	O*NET-SOC Code	Name of Occupation
1	Job Zone One – Little or No Preparation Needed	35-3022.00	Counter Attendants, Cafeteria, Food Concession, and Coffee Shop
		47-2051.00	Cement Masons and Concrete Finishers
2	Job Zone Two – Some Preparation Needed	33-2011.02	Forest Firefighters
		35-2014.00	Cooks, Restaurant
		35-2015.00	Cooks, Short Order
		35-3031.00	Waiters and Waitresses
		35-9031.00	Hosts and Hostesses, Restaurant, Lounge, and Coffee Shop
		39-6011.00	Baggage Porters and Bellhops
		39-9011.00	Childcare Workers
		41-2011.00	Cashiers
		43-4121.00	Library Assistants, Clerical
		47-2021.00	Brickmasons and Blockmasons
		49-9044.00	Millwrights
		53-3021.00	Bus Drivers, Transit and Intercity
		53-3041.00	Taxi Drivers and Chauffeurs
3	Job Zone Three – Medium Preparation	27-4011.00	Audio and Video Equipment Technicians
		33-2021.02	Fire Investigators
		33-3021.02	Police Identification and Records Officers

	Needed		
4	Job Zone Four – Considerable Preparation Needed	11-2011.00	Advertising and Promotions Managers
		11-9031.00	Education Administrators, Preschool and Childcare Center/Program
		17-1021.00	Cartographers and Photogrammetrists
		17-2111.01	Industrial Safety and Health Engineers
		17-2151.00	Mining and Geological Engineers, Including Mining Safety Engineers
		25-2012.00	Kindergarten Teachers, except Special Education
		25-2021.00	Elementary School Teachers, except Special Education
		25-2022.00	Middle School Teachers, except Special and Career/Technical Education
		25-2031.00	Secondary School Teachers, except Special and Career/Technical Education
		25-2032.00	Career/Technical Education Teachers, Secondary School
		25-3011.00	Adult Basic and Secondary Education and Literacy Teachers and Instructors
		25-4013.00	Museum Technicians and Conservators
5	Job Zone Five – Extensive Preparation Needed	11-9032.00	Education Administrators, Elementary and Secondary School
		11-9033.00	Education Administrators, Postsecondary
		19-1023.00	Zoologists and Wildlife Biologists
		19-2043.00	Hydrologists
		21-1012.00	Educational, Guidance, School, and Vocational Counselors
		25-4012.00	Curators
		25-9031.00	Instructional Coordinators

To measure the changes in skills, skill elements can be rated according to level (LV) needed and the importance (IM). The two values of IM and LV can be weighted and added up, forming a single index. The single index, which is called skill significance (SG) in this study, is calculated as $SG = w1 * IM + w2 * LV$, in which the weights w1 and w2 have been set to 1. This calculation was performed for both 2003 and 2018. Hence, a new dataset was created for each year (Step [d] of Figure 4.1). With these two datasets, the skill significances of the two years were compared to understand the changes over time. The differences between 2003 and 2018 were calculated by subtracting the skill significance of 2003 from that of 2018 (Step [e] of Figure 4.1).

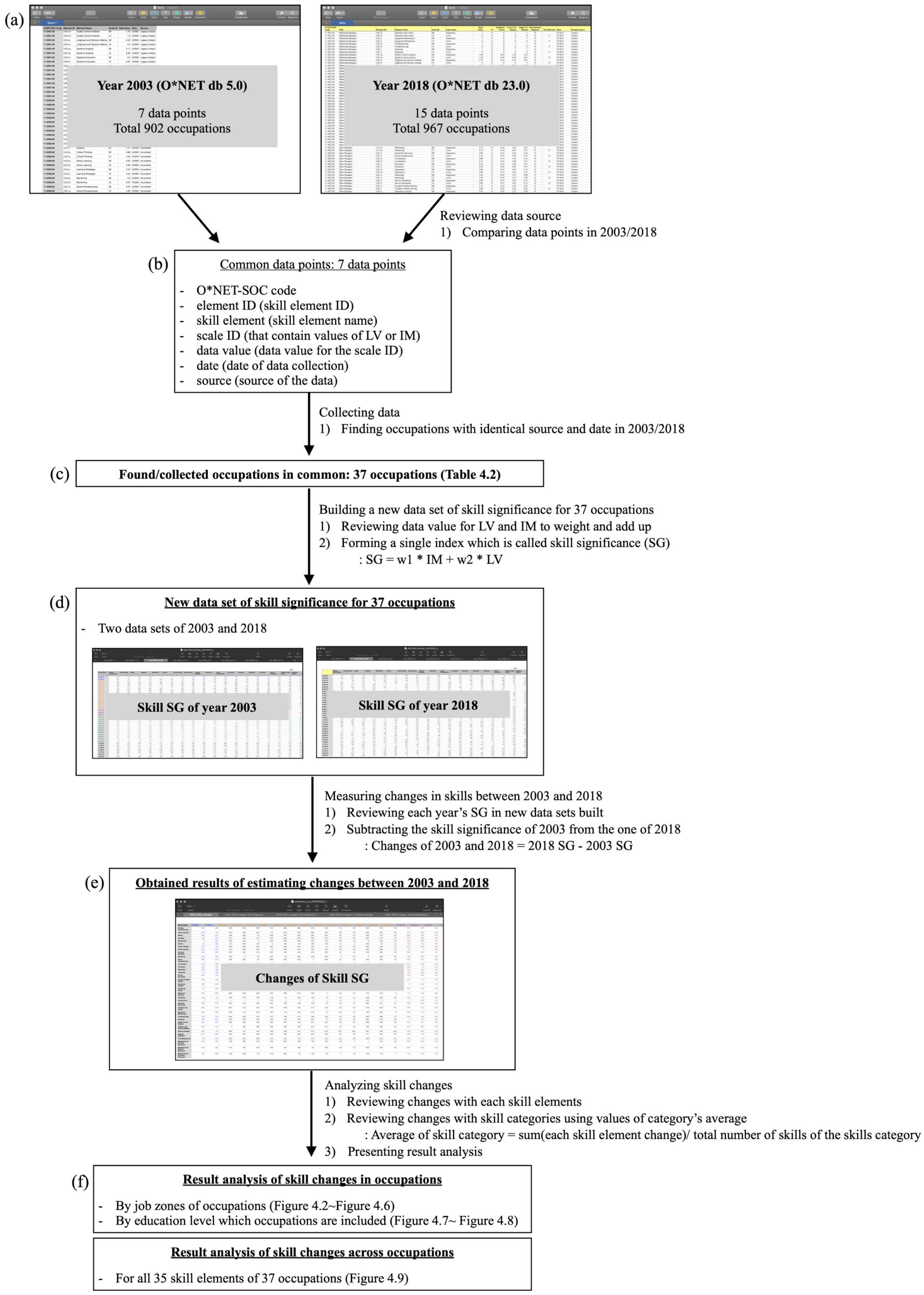


Figure 4.1 Process of data collection and analysis

4.4 Analysis of changes in skills

To answer RQ1, regarding how the skills required in occupations have changed over time within groups of occupations, the changes in skill significance for each skill element were calculated as the differences between skill significance in 2003 and in 2018. The analysis results are presented for different groups of occupations (Step [f] of Figure 4.1). First, the changes in skill significance are presented according to job zones (Section 4.4.1). Second, the results are presented according to the formal education level (Section 4.4.2). Finally, the skill-element changes are presented, with the highest values identified according to the skill category (Section 4.4.3).

4.4.1 Changes of skills in occupations belonging to specific job zones

The changes in skills (i.e., changes of skill significance) in occupations are presented according to occupational groups (Job Zone), as defined by the O*NET. As the 37 occupations are spread across all five job zones, the analysis covers each zone.

The results for Job Zone 1 are in Figure 4.2, for Job Zone 2 in Figure 4.3, for Job Zone 3 in Figure 4.4, for Job Zone 4 in Figure 4.5, and for Job Zone 5 in Figure 4.6. The x-axes of all graphs show 35 skill elements grouped into seven skill categories: content, process, social skills, complex problem-solving, technical skills, system skills, and resource-management skills. The y-axis displays the changes in skill significance. The data points in the graphs are close to the line of zero if there is almost no change in skill significance.

If the data points are found above/below the zero line, skills are considered more/less significant in 2018 than in 2003. For example, in Figure 4.2, the skill element of complex problem-solving displays increased skill significance for two occupations (counter attendants and cement mason). These results mean both skill elements were recognized more significantly in 2018. Moreover, the skill change is more significant for counter attendants than cement masons.

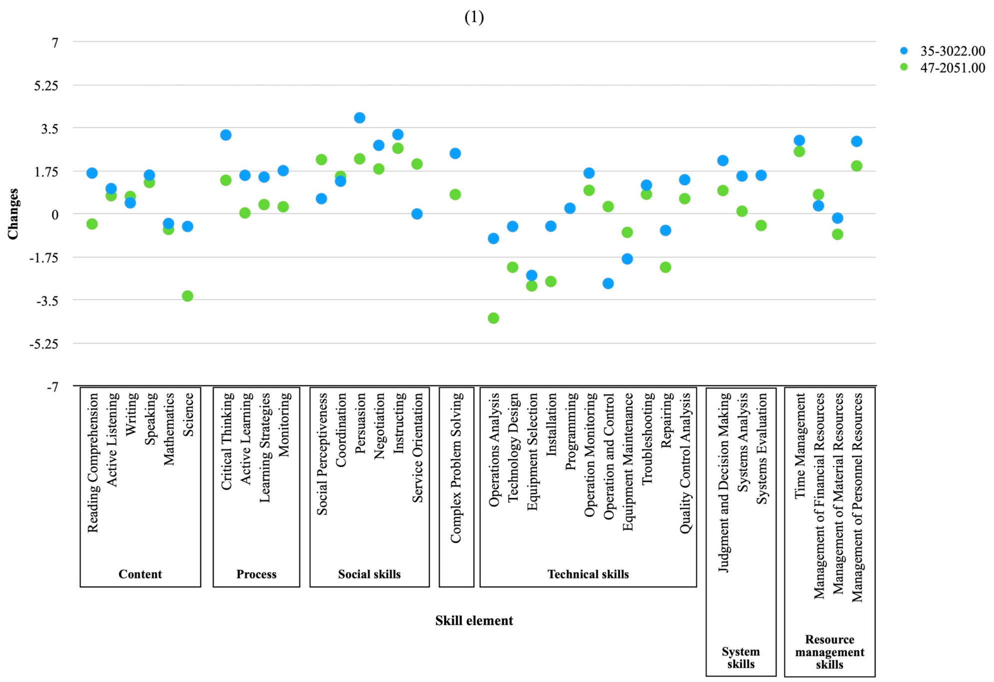


Figure 4.2 Changes in skill significance for two occupations belonging to Job Zone 1

Analysis of Job Zone 1 occupations: The results for the two occupations belonging to Job Zone 1 of the O*NET occupation classification are depicted in Figure 4.2. Considering the changes in skill significance, both occupations display similar trends regarding the skills needed in 2018 compared with 2003. Regarding three skill categories (process, social skills, and complex problem-solving), all the skill elements display increased skill significance. The largest decreases are among technical skills. A summary of the changes is provided in Table 4.3.

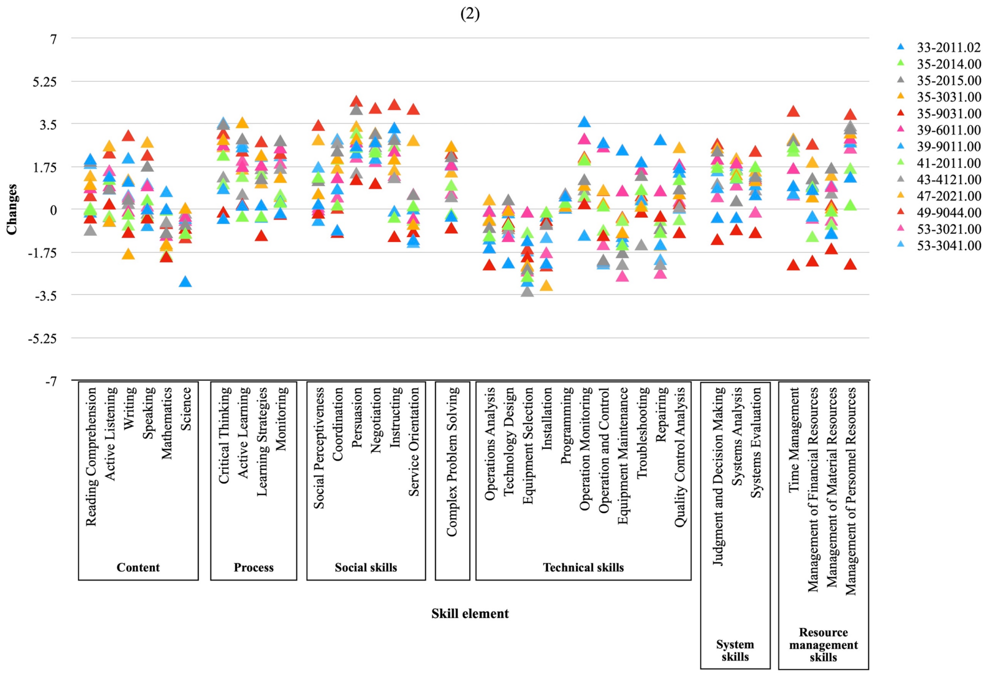


Figure 4.3 Changes in skill significance for 13 occupations belonging to Job Zone 2

Analysis of Job Zone 2 occupations: In Figure 4.3, 13 occupations are presented that are included in Job Zone 2 of the O*NET occupation classification. Eight skill elements did not change. These skill elements are science for one occupation (waiters and waitresses), coordination for one occupation (millwrights), quality control analysis for one occupation (taxi drivers and chauffeurs), technology design for one occupation (bus drivers: transit and intercity), and programming for four occupations (childcare workers, brickmasons and blockmasons, bus drivers: transit and intercity, and taxi drivers and chauffeurs). This is the only job zone that includes zero changes for some skill elements. The remaining skill elements (except for a few technical skill elements and content skills) for the occupations in Job Zone 2 depicting skill significance increased between 2003 and 2018. The skill changes related to process, social skills, complex problem-solving, and resource-management skills tended to increase (Table 4.3).

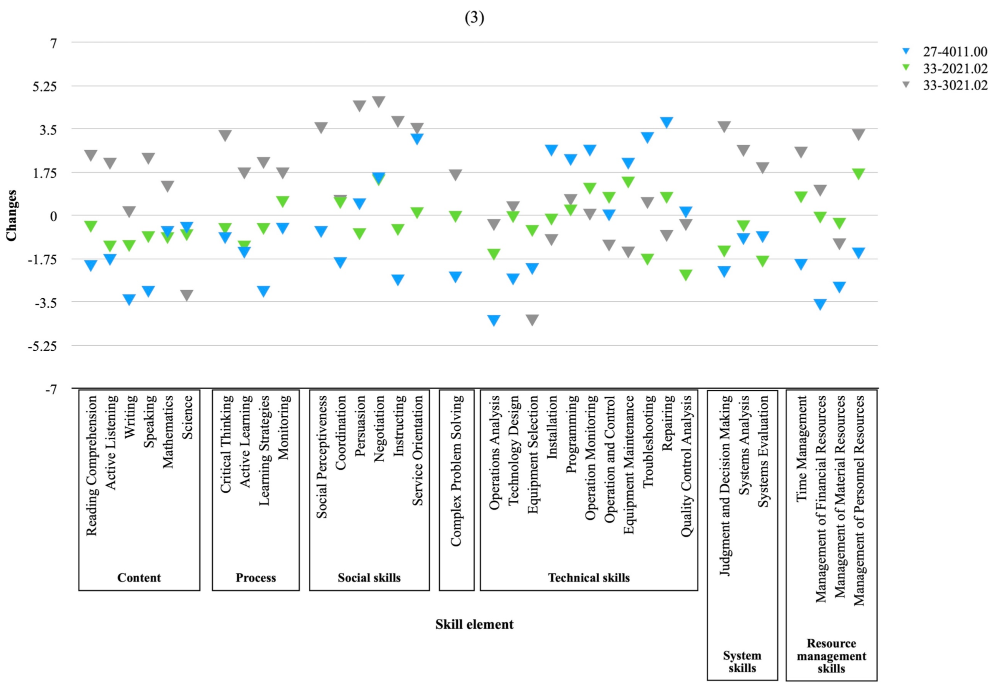


Figure 4.4 Changes in skill significance for three occupations belonging to Job Zone 3

Analysis of Job Zone 3 occupations: The skill significance changes of three occupations that belong to Job Zone 3 of the O*NET's classification are presented in Figure 4.4. Every skill element for all three occupations depicts changes between 2003 and 2018. Regarding the changes in the technical skill category, most (i.e., eight out of 11) of the skill elements of the audio-video equipment technicians increased in significance compared with those of the other two occupations in 2018. The changes in the technical skills of the other two occupations either do not display a large variation in changes or show a decline. The changes for all the skill elements for the second occupation (fire investigator) are around the zero line. Finally, the skill elements (except for some technical skills) reveal increases between 2003 and 2018 for the third occupation (policy identification and records officers). Overall, it is difficult to identify a common pattern of changes in skill significance for the three occupations in Job Zone 3 (Table 4.3).

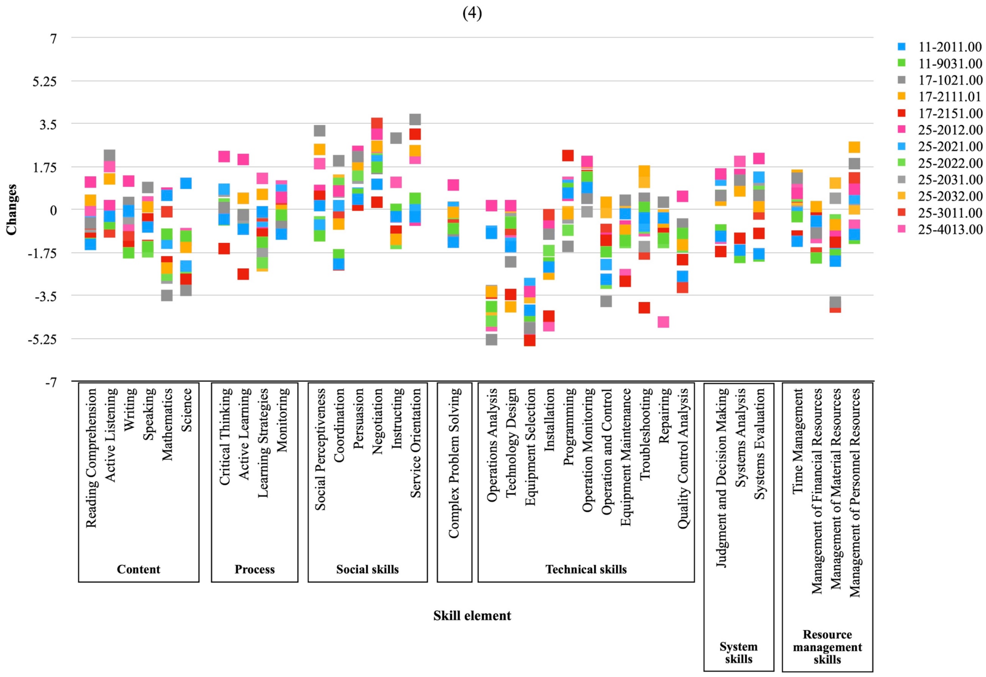


Figure 4.5 Changes in skill significance for 12 occupations belonging to Job Zone 4

Analysis of Job Zone 4 occupations: In Figure 4.5, 12 occupations are presented that are included in Job Zone 4 of the O*NET occupation classification. There are changes for all the skill elements for all occupations in Job Zone 4. Although the changes in the skill categories of process, complex problem-solving, and system skills are around the zero line, the significance of social skills increased for many occupations. In particular, two skill elements (persuasion and negotiation) are placed above the zero line. However, technical skills display low-skill significance for many occupations in 2018 (Table 4.3).

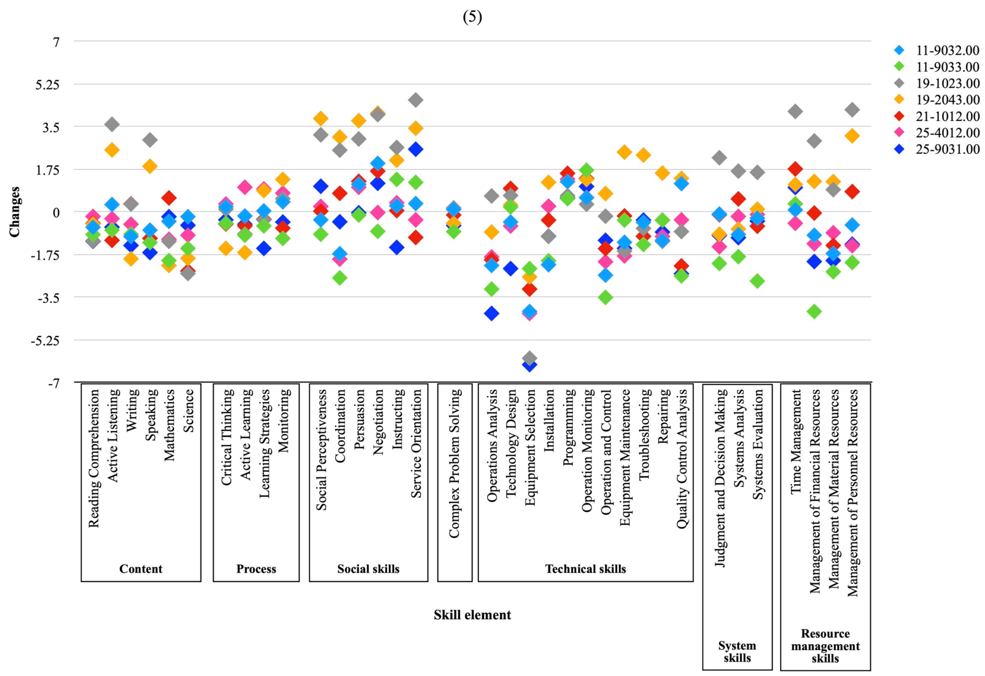


Figure 4.6 Changes in skill significance for seven occupations belonging to Job Zone 5

Analysis of Job Zone 5 occupations: The results for seven occupations belonging to Job Zone 5 of the O*NET occupation classification are depicted in Figure 4.6. The data points are around the zero line for most of the occupations in the two skill categories of process and complex problem-solving. Only the significance of social skills increased in 2018. However, the remaining skill categories, such as technical skills and content skills, are viewed as less significant in 2018 than in 2003 (Table 4.3).

Overall Analysis: The significance of almost all skills (i.e., except for the eight occupations in Job Zone 2) changed in occupations over time (Figure 4.2 to Figure 4.6). Moreover, the significance of skills changed differently for each occupation and skill element. Even for occupations within a job zone, the change of the significance for each skill element differs for each occupation.

Regarding the quantity of changes in skill significance, the changes in two skill categories are more obvious than in others. The skill category of social skills was considered more significant in 2018 than in 2003 (Row 3 of Table 4.3). This category displays positive changes on average for all occupations. The significance of technical skills was lower in 2018 than in 2003 (Row 5 of Table 4.3). This category displays decreases in changes on average for all occupations.

For the other five skill categories (content, process, complex problem-solving, system skills, and resource-management skills), the results are mixed, revealing either increasing or decreasing changes in skill significance for different occupations (Rows 1, 2, 4, 6, and 7 of Table 4.3). The skill category of content displays very small changes in general, but changes for occupations belonging to Job Zones 1 and 2 appear close to the zero line, and the changes for occupations belonging to Job Zones 3, 4, and 5 appear below the zero line (Row 1 of Table 4.3). Regarding the four skill categories of process, complex problem-solving, system skills, and resource-management skills, the skill significance changes for occupations belonging to Job Zones 1 and 2 increased more substantially than for the other three job zones (Rows 2, 4, 6, and 7 of Table 4.3).

In addition, the skill significance changes for Job Zones 1 and 2 mostly display a pattern of increasing on average, except for the skill category of technical skills (Columns 2 and 3 in Table 4.3). Job Zone 3 reveals an increase in skill changes for three skill categories (process, social skills, and system skills), and Job Zone 4 displays increased skill significance for two skill categories (social skills and system skills) generally. Furthermore, Job Zone 5 displays only one skill category's (social skills) significance increasing, and the category of resource management reveals a near zero change (Column 5 of Table 4.3).

Table 4.3 Observations from the analysis of skill changes for each skill category and job zone

Skill Categories	**Job Zone 1**	**Job Zone 2**	**Job Zone 3**	**Job Zone 4**	**Job Zone 5**
Content	0	0	–	–	–
Process	+	+	0	–	0
Social skills	++	++	+	+	+
Complex problem-solving	++	+	–	–	–
Technical skills	–	–	0	–	–
System skills	+	+	0	+	–
Resource-management skills	+	+	0	–	0

*Note: The rating values are based on mean significance changes: If 'mean' ≤ 0.2 or 'mean' ≥-0.2, then it is represented as '0.' If 'mean' > 0.2 and 'mean' ≤ 1.5, then it is represented as '+.' If 'mean' < -0.2 and 'mean' ≥ -1.5, then it is represented as '-.' If 'mean' > 1.5, then it is represented as '++.' If 'mean' ≤ -1.5, then it is represented as '–.'

Overall, technical skills became less significant. Surprisingly, however, social skills became more significant across all job zones. Furthermore, regarding the remaining skills, occupations belonging to Job Zones 1 and 2 displayed increased significance with process, complex problem-solving, system skills, and resource-management skills. Occupations belonging to Job Zone 3 had small changes, whereas occupations belonging to Job Zones 4 and 5 exhibited a decrease in skill significance.

4.4.2 Changes of skills in occupations belonging to specific formal education groups

In this section, job zones and the occupations belonging to them are divided according to the level of formal education they require. A bachelor's degree was taken as the threshold. The occupations belonging to Job Zones 1, 2, and 3 require less than a bachelor's degree (i.e., high school or lower). The occupations in Job Zones 4 and 5 require a bachelor's degree or higher formal education level. Applying this classification to the 37 occupations at focus, the group with a low formal-education level includes 18 occupations. The group with a high formal-education level includes 19 occupations.

The results of the analysis of both groups are presented in Figures 4.7 and 4.8. The x-axes represent skills (i.e., skill elements in Figure 4.7 and skill categories in Figure 4.8), and the y-axes represent the skill changes (Figure 4.7 and right graph of Figure 4.8) and the absolute values of skill significance (left graph of Figure 4.8). The values for each skill are the averages for each group of occupations. The circles represent the average changes for the low formal-education group. The triangles are the average changes for the high formal-education group.

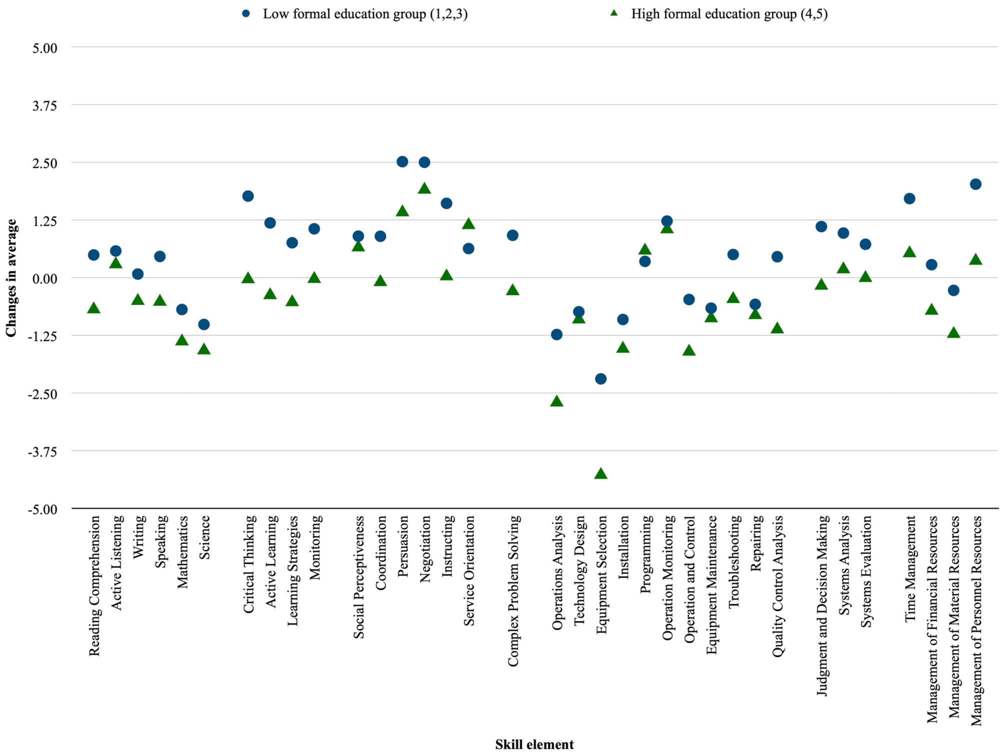


Figure 4.7 Changes in skill significance for skill elements in occupations in the low formal-education group (circles) and the high formal-education group (triangles)

As is evident in Figure 4.7, the skill elements, which are higher than the zero line except for two (service orientation and programming), are positioned above the triangles. This positioning means the skill changes in occupations of the low formal-education group were larger than those of the high formal-education group. This outcome reveals that almost all skill elements in the low formal-education group became more important in 2018 compared with 2003. Regarding the skill elements below the zero line, the skills of the low formal-education group changed little, retaining their significance. Analyzing the skill changes for skill categories, this difference is even more obvious (left graph of Figure 4.8).

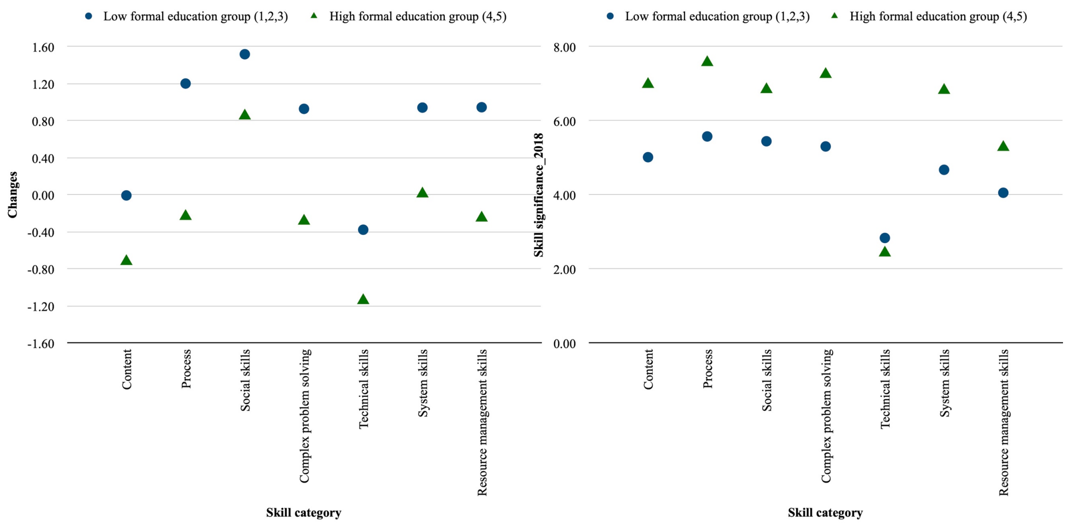


Figure 4.8 Changes in skill significance (left graph) and skill significance in 2018 (right graph) for skill categories in occupations belonging to the low formal-education group (circles) and those belonging to the high formal-education group (triangles)

The left graph of Figure 4.8 reveals the largest skill changes for the high formal-education group are in the skill categories of content, social skills, and technical skills. Although the skill changes belonging to the social skills category display an increase in significance, the significance for the categories of content and technical skills is clearly reduced. The changes for the low formal-education group are even higher for the social skill category but less for the categories of content and technical skills. Although the skill changes of the high formal-education group regarding the remaining skill categories do not reveal large changes (i.e., the values are below but close to the zero line), the skill changes of the low formal-education group have increased. This point is supported by the right graph of Figure 4.8, in which the absolute values of the skill significance for 2018 are illustrated. The skill significance of all the skill categories (except for the technical skill category) for the high formal-education group is higher than for the low formal-education group. Although it is surprising the skill significance for the content category is quite high (right graph of Figure 4.8), it is evident this category has already lost significance (left graph of Figure 4.8).

However, overall, the grouping of occupations according to high and low formal-education does not indicate any clear difference in skill significance or change in skill significance regarding skill elements or skill categories.

4.4.3 Changes of skills averaged over occupations for all skills

The changes in skill significance for all skill elements and all 37 occupations are listed in Figure 4.9. On the x-axis, the 35 skill elements are listed with the skill category. Only the first word of each skill category is added to the figure. The y-axis contains the differences in skill significance between 2003 and 2018. The dots represent occupations and are colored according to the job zones they belong to: Job Zone 1 is blue, Job Zone 2 is orange, Job Zone 3 is plum, Job Zone 4 is green, and Job Zone 5 is black. The skill elements on the x-axis are sorted according to the size of the mean value of the skill changes, starting with the largest one on the left-hand side. The thick gray line connects the mean value of each skill element. For example, the first skill element on the x-axis (negotiation) has the highest mean value, and the final element (equipment selection) has the lowest mean value of all the skills.

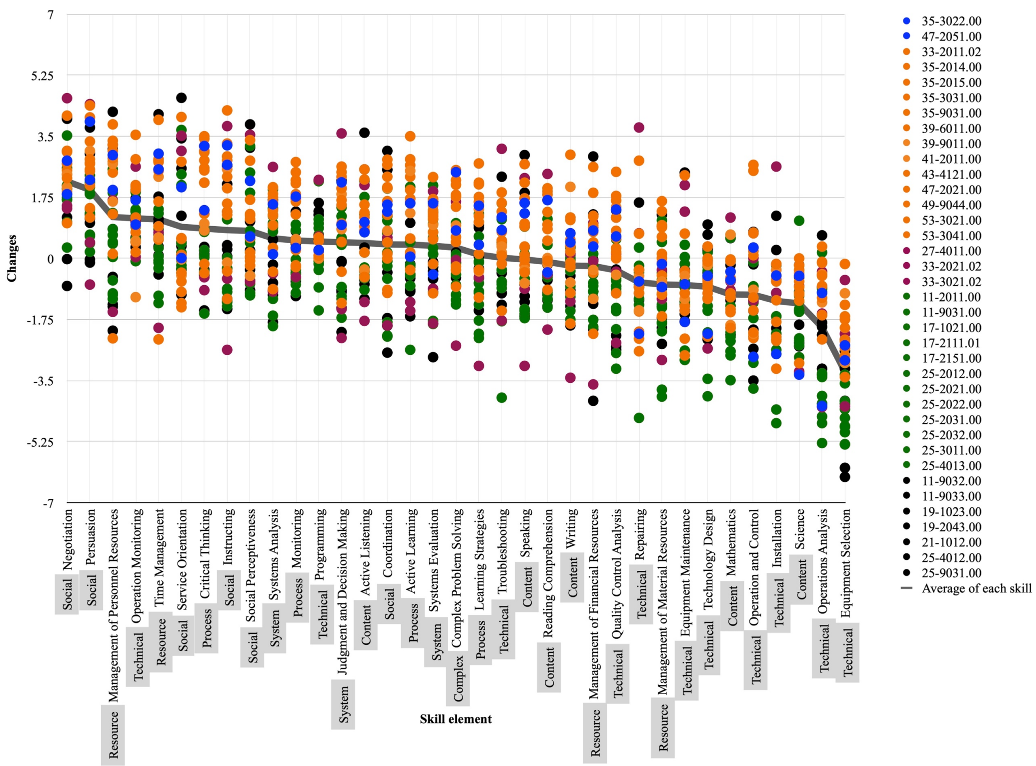


Figure 4.9 Changes in skill significance for all 37 occupations, all 35 skill elements, and all seven skill categories

The mean value line in Figure 4.9 illustrates the significance has increased on average for 20 of the 35 skill elements, marked by the skill element of negotiation on the left-hand side and the skill element of troubleshooting in the middle of the graph. The second group contains the 15 skill elements, from speaking to equipment selection.

Regarding the first group of 20 skill elements, all the elements of two skill categories (social skills and process) are included, meaning the significance of these skill elements increased for many occupations from 2003 to 2018. Among these increases, the two skill elements (negotiation and persuasion) from the skill category of social skills displayed the greatest changes. Moreover, the skill element of negotiation displayed an increase in skill significance for all occupations except for two (the two dots below the zero line in Figure 4.9). The skill element of persuasion had the second largest increase in changes. Persuasion became more significant for 34 of the 37 occupations. The two skill elements of management of personnel resources and operation monitoring in third and fourth positions, respectively, belong to the skill categories of resource management and system skills. From this point, the slope goes down steadily.

Regarding the second group, the skill element of equipment selection exhibited the greatest decrease in skill significance; its value decreased for all 37 occupations. Furthermore, only 13 out of 17 skill elements belonging to the two skill categories of content and technical skills were in the second group of skill elements that had a decline in skill significance from 2003 to 2018.

Overall, the grouping of skill elements into skill categories does not provide a clear explanation for the change in skill significance for all skill elements, as all the skill categories except for social skills contain some skill elements that displayed an increase in skill significance, whereas other skill elements displayed a decrease in skill significance.

4.4.4 Discussion of results: skill changes

To answer RQ1 (How have the skills required to perform an occupation changed over time?), the observations were interpreted in the preceding subsections of 4.4.1, 4.4.2, and 4.4.3. Overall, skill changes are evident across all occupations and popular groupings (Figure 4.2 to Figure 4.9). Although this result is unsurprising, as it was expected the skills required to perform an occupation adapted to the new requirements over the course of 16 years, this result is meaningful in the research area. Only a few studies have found changes in skills in occupations and in groupings of occupations. For example, Alabdulkareem et al. (2018) conducted a form of skill comparability between occupations by following the same worker's job transition to reveal how skills are related between occupations. The results of this present study contribute to these findings by revealing that skills (required to perform tasks in an occupation) are structured differently regarding changes in skill significance after years.

Moreover, and most interestingly, 20 skill elements became more significant on average across all occupations (Figure 4.9). All the skill elements of the skill category of social skills became more significant, and most of the skill elements of the skill categories of content and technical skills became less significant (Figure 4.9). Regarding the remaining four skill categories, no such statement can be made, as some of the skill significance changes of skill elements increased and some decreased.

Examining the changes in skills in the groups of occupations, for example, grouped according to job zone (Figure 4.2 to Figure 4.6), formal education level (Figure 4.7 and Figure 4.8), or skill category (Figure 9), no clear characteristics emerged. The skill changes for each occupation within a single group are all different. It can be noted only that the technical skills became less significant in each of these groups, and social skills became more significant. Thus, the groupings regarding job zones, formal education level, or skill category do not help to explain the skill changes observed.

Consequently, as the observed skill changes are expected to impact any analysis of the labor market and predictions of the employability of labor, it is necessary to find a way to classify the observed changes in skill significance.

4.5 Analysis of skills: the classification of skill elements for capturing changes in skill significance changes and their impact

Regarding the findings in Section 4.4, it should be questioned whether there is a proper approach that can describe each occupation individually regarding skills. In this section, a grouping scheme is proposed to capture the observations made in the previous Section 4.4.

4.5.1 Classification of skill elements regarding tacit and explicit knowledge

As skills can be classified into tacit and explicit skills, every occupation can be described according to its share of these skills. These two types of knowledge, tacit and explicit, were defined by Polanyi (1966). Tacit knowledge is difficult to describe and share using definite language, but explicit knowledge can be explained and documented using structured language (Polanyi, 1966). Following this line of thought, any skill with the characteristics of tacit knowledge is difficult to substituted for or replace by technology. Any skill with the characteristics of explicit knowledge is simpler to substitute for or replace by technology. Skills such as persuasion and negotiation from the skill category of social skills are typical examples of tacit skills, and skills such as troubleshooting from the skill category of technical skills are examples of explicit skills.

Since the O*NET's skill elements are well defined, the 35 skill elements for this study's model are highly suitable. However, the O*NET's skill elements are designed for the US labor market. Therefore, the definitions might not be precisely applicable to other contexts.

To classify the skill elements into tacit and explicit, two aspects were considered. First, Polanyi's (1966) definitions of tacit and explicit knowledge were applied. Second, the definitions of Spitz-Oener (2006) regarding routine and non-routine tasks was used. Spitz-Oener (2006) defines tasks as routine or non-routine tasks, depending on whether the task can be codified or performed by machines. Based on these two references, the criterion for distinguishing between tacit and explicit skills is whether the skill (i.e., the knowledge or skill required to perform a task) can clearly be captured (e.g., by describing it in textual form) and obtained by anyone who wants to obtain the skill. Following this definition, all 35 skills were examined regarding whether that skill element can be explained and described using a manual. Table 4.4 contains the results of classifying the skill elements into tacit or explicit skills. For the classification, the full O*NET descriptions for each skill element were used (Appendix D).

Table 4.4 Classification of skill elements into tacit and explicit, based on the O*NET information, the definitions of Polanyi (1966), and the definitions of Spitz-Oener (2006)

Skills Subcategory	**Skill Element**	**Author Classification of Tacit and Explicit**	**Justification (This skill is interpreted to be used for following needs:)**
Content	Active Listening	**T**	to understand and communicate with people properly in undefined and unpredictable circumstances
	Mathematics	**E**	to solve problems using mathematics following defined steps
	Reading Comprehension	**E**	to read and understand written contents
	Science	**E**	to solve problems with certain scientific principles
	Speaking	**T**	to talk to other people for communication and information
	Writing	**T**	to understand and communicate with people properly through

			written contents
Process	Active Learning	**T**	to contribute to learning new things by comprehending conditions and situations in the present and future
	Critical Thinking	**T**	to resolve issues by analyzing circumstances logically
	Learning Strategies	**T**	to decide upon and organize appropriate methods to learn new things
	Monitoring	**T**	to review performances and results for oneself and others
Social skills	Coordination	**T**	to organize different people and activities by efficiently relating to others
	Instructing	**T**	to guide and teach how to do things
	Negotiation	**T**	to reach an understanding and agreement by settling differences
	Persuasion	**T**	to talk someone into doing something or to change other's thinking or behavior
	Service Orientation	**T**	to look around actively to help others
	Social Perceptiveness	**T**	to notice and understand easily the circumstances relating to people
Complex problem-solving	Complex Problem-Solving	**T**	to manage a series a complex problem-solving process, such as defining the problem,

			identifying the causes, reviewing the conditions and options, selecting and implementing the solution
Technical skills	Equipment Maintenance	**E**	to perform usual maintenance
	Equipment Selection	**E**	to select proper tools and equipment
	Installation	**E**	to install machines, programs, etc. according to their specified requirements
	Operations Analysis	**T**	to analyze current operating conditions to improve or create a design
	Operation and Control	**E**	to operate and control machines, programs, and systems
	Operation Monitoring	**E**	to review performances and results to check that machines, programs, and systems are functioning properly
	Programming	**T**	to write computer programs
	Quality Control Analysis	**E**	to review and inspect the performances and qualities of working processes, products, and services
	Repairing	**T**	to repair machines using tools
	Technology Design	**T**	to make or develop technology and machines to meet users' needs
	Troubleshooting	**E**	to determine and fix technical errors

System skills	Judgment and Decision-Making	**T**	to select and decide the most appropriate solution by considering the resources, conditions, and results of the solution
	Systems Analysis	**T**	to review systems and their related factors to determine system changes and improvements
	Systems Evaluation	**T**	to evaluate system performances to meet the purposes of systems by correcting and improving performances and system environments
Resource-management skills	Management of Financial Resources	**T**	to plan and organize how to spend money to meet the purposes of works and to account for expenses
	Management of Material Resources	**E**	to plan and organize how to use resources regarding machines, facilities, and equipment to meet the purposes of works
	Management of Personnel Resources	**T**	to plan and organize how to deploy people by distinguishing their best skills and directing and developing them to do jobs
	Time Management	**T**	to plan and organize how to use time for oneself and working with others

Using the classification of the skill elements in Table 4.4, the skill elements in Figure 4.9 were labeled, as illustrated in Figure 4.10.

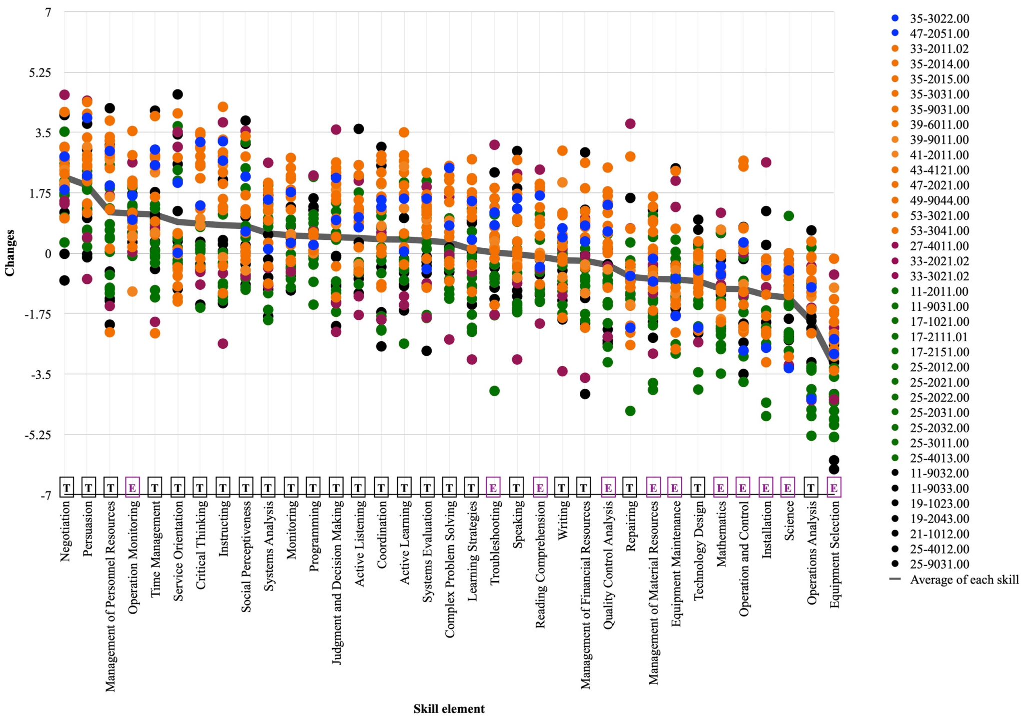


Figure 4.10 Changes in skill significance for all 37 occupations and for all 35 skill elements, classified into tacit and explicit skills

In Figure 4.10, the majority of the skills identified as tacit are on the left-hand side of the axis. On the left-hand side are 20 skill elements whose significance increases with their changes. Among these 20 skill elements, 18 are identified as requiring mostly tacit knowledge. Only two skills, operation monitoring and troubleshooting, are considered explicit. For example, negotiation is considered whether the skill is required for routine and codified tasks and whether the skill can be presented and learned easily from textbooks. Following the definition of negotiation in the O*NET, negotiation is 'bringing others together and trying to reconcile differences' (Appendix D). Therefore, the skill is required for non-routine tasks and involves an unexplainable process. Naturally, most of the skills identified as tacit fall into the categories of social skills, complex problem-solving, and processes. These skill categories include skills that have become more significant over time across occupations. On the right-hand side are 15 skill elements, from speaking to equipment selection, which are decreasing. Among these 15 skill elements, nine require mostly explicit knowledge, and six are tacit. Among them, 9 skill elements are identified as requiring a majority of explicit knowledge and 6 skill elements are found as tacit. There are total 11 explicit skills defined and most of the explicit skills (nine of 11) are on the right-hand side of the x-axis, which means their significance decreased during the period between 2003 and 2018. These observations reveal a tendency for skills requiring explicit knowledge to be less important than skills identified as tacit.

4.5.2 Discussion of results

Regarding RQ2 (How can skill-element significance be used and skill elements be aggregated to simplify their use?), a simple way to group skill elements by using tacit and explicit knowledge classification was found.

The classification of skill elements regarding tacit and explicit knowledge provides a simple way to describe skills instead of the educational level of employees. However, with further technological developments, skills might be classified differently, as the number of explicit skills may increase.

This discussion of the results reveals that, First, the skills that human labor takes for a comparative advantage (i.e., tacit skills) are more significant across occupations compared with the skills that can be automated (i.e., explicit skills); second, since these results apply across occupations, explaining skills should not be limited to the formal education level.

4.6 Using skill-element significance to predict how technological advancement impacts salary level and productivity

Traditionally, labor skills are measured using the level of formal education. Education is a convenient way to measure the skills of workers by using data on school enrollment, costs and expenses for education and training, and income through degrees obtained (Abraham & Mallatt, 2022).

Based on their formal education level, workers are divided into two groups: high-skilled (i.e., college or higher education) and low-skilled (i.e., high school or lower) workers (Autor, Goldin, & Katz, 2020; Autor et al., 2003; Frey & Osborne, 2017; Goldin & Katz, 2007; Spitz-Oener, 2006). A worker with a high level of education has been considered one whose productivity is high. In this way, the education certificate works as a signal in the labor market, as a worker holding a degree from a higher-education institute is regarded as being more productive and deserving of higher earnings (Borjas, 2020).

However, if the formal education level is the only major factor considered when discussing skills, this discussion is limited and prone to erroneous conclusions. The formal education level does not consider (or even neglects) workers' skills regarding their abilities to perform tasks (as explained in previous chapters of this study). Consequently, as detailed characteristics are missing, any observation or phenomenon within the same level of education cannot be explained. For example, Autor, Goldin, and Katz (2020) extended the study of Goldin and Katz (2007) by using more recent data. One finding of their study is there has been a growing inequality of wages within the same level of education since 2000 (Autor et al., 2020). An explanation for this gulf is not (and cannot be) provided, since it cannot be explored due to a lack of data for the same educational level. Moreover, skills that are difficult to explain through formal education cannot be reflected in existing models. The only study that extends the existing view is Deming (2017), which uses social skills as an explanatory variable in its aggregate model. The information about skill significance and the changes in skill significance, as in this present study, supersedes that in existing studies and demonstrates that valuable information is available that could make aggregate models more precise.

The literature has emphasized the importance of creative tasks based on the assumption that technology development continues (Frey & Osborne, 2017) and that non-routine tasks require interactive communication skills, resilience, and problem-solving skills (Autor, 2015). In particular, in previous studies, social skills have been considered important (Deming, 2017), skills have been studied based on skill complementarity between occupations (Alabdulkareem et al., 2018), and probable job transitions have been suggested by studying the skills of truck drivers (Van Fossen et al., 2022). In these studies, these types of skills have been considered more important than formal education. The results of this present study reveal that other descriptions of skills can be used to explain workers' ability to perform tasks. Moreover, such skills are required.

In this study, the skills required to perform tasks were divided into tacit and explicit skills according to the characteristics of each skill (Table 4.4). Of the 35 skill elements in the O*NET, 24 were defined as tacit and 11 as explicit. This grouping is based on what is currently believed to be possible to learn through clear instructions. However, the proportion of tacit and explicit skills might change as technology evolves. According to the current classification, 18 of the 20 skills that increased in significance from 2003 to 2018 had tacit features, accounting for 75% of the total 24 tacit skills (Figure 4.9). Nine of the 11 explicit skills belonged to the group of skills that decreased in significance between 2003 and 2018.

The reason for considering wages among the employment-related indicators is that education is a factor in human capital investment, and studies have found that education is related to workers' earnings (Borjas, 2020; Lemieux, 2006). Therefore, it is assumed that, if skills, defined by knowledge type, can explain wages (if linearly related; Section 4.6.1), this indicator can be used as a proxy for education to explain the relative demand for workers in a production function (Section 4.6.2).

4.6.1 Use of tacit and explicit knowledge classification regarding salary prediction

The changes in skill significance in occupations and across occupations might also be helpful for explaining wage growth in greater detail. For example, Autor and Dorn (2013) noted that real wage growth in occupations related to services increased more rapidly than in other occupations with low formal education. Analyzing the skills required might reveal the different skills needed to perform the tasks. Although service occupations might require certain social skills, other occupations with a low formal-education level might not.

This section offers an indication of how the information about tacit and explicit skills might impact the salaries of workers. The average level of significance for tacit and explicit skills is related to the annual mean salary from 2018 (Figures 4.10 and 4.11). The year's salary data were collected from the Occupational Employment and Wage Statistics of the U.S. Bureau of Labor Statistics. The data table of May 2018 is used.[10] In both figures, each occupation's salary is presented as its percentage compared with the occupation with the highest salary in the year (anesthesiologists, and the mean value is 267,020 US dollars). In both figures, the average values of significance for tacit and explicit skills in 2018 are on the y-axis, and the salary data in percentage for occupations are presented on the x-axis. The 37 occupations collected in this study are in the rather low- and medium salary range compared with the highest of the year. Among the 37 occupations, advertising and promotion managers from Job Zone 4 received the highest salary, but this was only 50% of

[10] U.S. Bureau of Labor Statistics, 'Occupational Employment and Wage Statistics', accessed April 19, 2023, https://www.bls.gov/oes/tables.htm

the year's highest.

4.6.1.1 Effect of tacit skills on salary in 2018

On the left-hand side of Figure 4.11, the average of tacit skills is related to the mean salary of 2018 for each occupation. This scatter diagram illustrates the distribution of tacit skills and salaries. From left to right, the average of tacit skills is going upward as salary increases. On the right-hand side of Figure 4.11, the same information is presented, except for sorting the salaries in increasing order. The dots are the average values of the tacit skills, and the bars are each occupation's salary. In general, higher salary values correlate with a higher significance of tacit skills, regardless of their job zones.

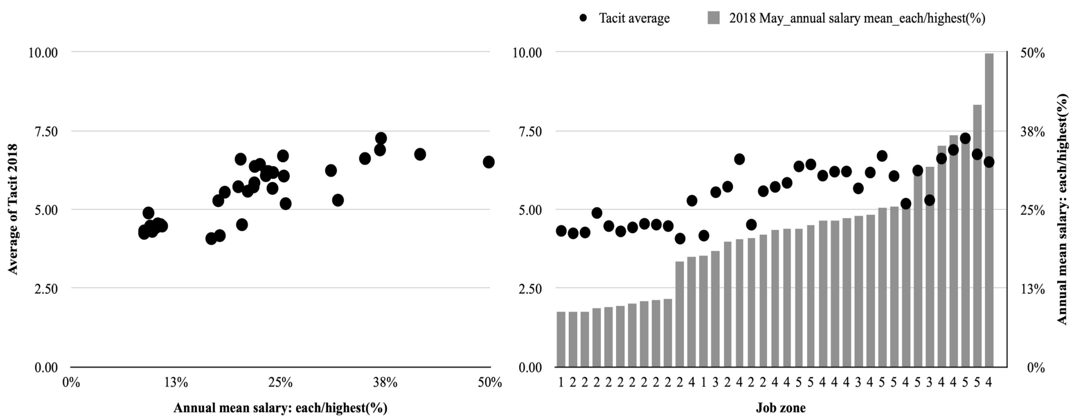


Figure 4.11 Significance of tacit skills and salary in 2018

(Label description: 'Average of Tacit 2018' – average value of significances for the group of tacit skills in 2018; 'Annual mean salary: each/highest (%)' – percentages estimated 2018's mean salary for 37 occupations collected for this study compared with the occupation with the highest salary in 2018 in the data table of BLS; 'Job zone' – annual mean salary for each occupation presented by marking their job zones.)

4.6.1.2 Effect of explicit skills on salary in 2018

On the left-hand side of Figure 4.12, the average of explicit skills is related to the mean salary of 2018 for each occupation. From left to right, the average of explicit skills is grouped at some salary points, but they are too randomly dispersed to discuss their correlation. On the right-hand side of Figure 4.12, the levels of explicit skills are in increasing order of the salaries. The dots are the average values of the explicit skills, and the bars are each occupation's salary. It is difficult to say there is any general pattern between explicit skills and salary, but explicit skills are considered differently in each occupation regardless of job zone and salary.

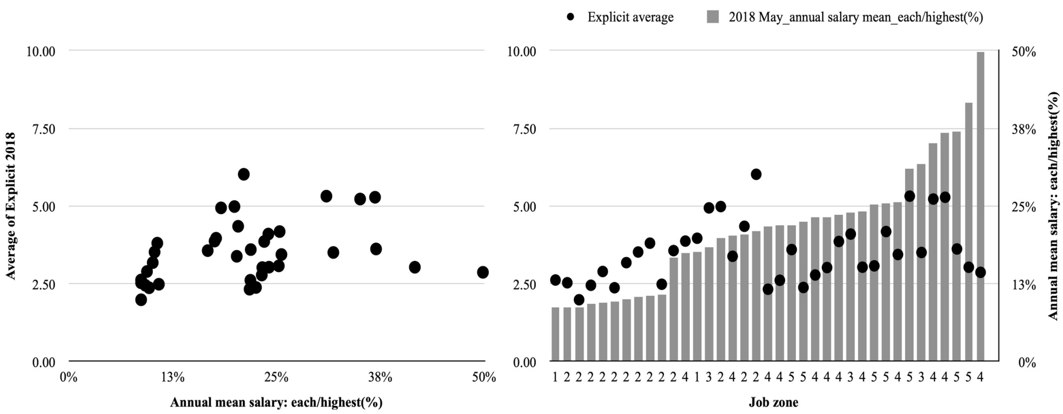


Figure 4.12 Significance of explicit skills and salary in 2018

(Label description: 'Average of Explicit 2018' – average value of significances for the group of explicit skills in 2018; 'Annual mean salary: each/highest (%)' – percentages estimated for 2018's mean salary for 37 occupations collected for this study and compared with the occupation with the highest salary in 2018 in the data table of BLS; 'Job zone' – annual mean salary for each occupation presented by marking their job zones.)

4.6.1.3 Discussion of results: effect of skills on salary

Drawing scatter diagrams of skills based on tacit and explicit knowledge and salary revealed their relationships in Figures 4.11 and 4.12. A regression analysis was conducted to verify these relationships. The annual mean salary (or its logarithm) was the dependent variable, and the average significance of tacit and explicit skills was an independent variable. For the analysis, IBM SPSS Statistics version 29.0 was used.

Table 4.5 presents the results. The variables are titled ‘annualmean2018may,’ which is the annual mean salary for each occupation. ‘Eaverage’ is the average significance of explicit skills, and ‘Taverage’ is the average significance of tacit skills. The results confirm a relationship between tacit skills and wages at the 0.001 significant level (Model 1 and Model 2). However, the results are not significant for explicit skills and wages.

Table 4.5 Output of regression analysis regarding annual salary and tacit and explicit skills (Models 1 and 2)

	Unstandardized Coefficients		Standardized Coefficients		
Model 1	B	Std. Error	Beta	t	Sig.
(Constant)	-72935.423	17046.800		-4.279	<.001
Eaverage	3238.230	2858.414	.120	1.133	.265
Taverage	21550.255	2982.629	.764	7.225	<.001
Model summary: R^2(adj. R^2)= .647(.626), F= 31.155			$Y_{Salary} = \beta_0 + \beta_1 X_{Eaverage} + \beta_2 X_{Taverage} + \varepsilon$		

a. Dependent Variable: annualmean2018may

Model 2		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
	(Constant)	-66511.010	16140.852		-4.121	<.001
	Taverage	22453.097	2885.800	.796	7.781	<.001
Model summary: R^2(adj. R^2)= .634(.623), F= 60.537				$Y_{Salary} = \beta_0 + \beta_1 X_{Taverage} + \varepsilon$		

a. Dependent Variable: annualmean2018may

A similar analysis to that in Models 1 and 2 was performed using the logarithm of the salary in 2018, and the results are in Table 4.6. The results indicate a strong correlation in both models, with significance levels below 0.001 and 0.05. Model 3 is preferred because it has the best statistical results, with an r-square of 0.725. Regarding Model 3, collinearity tests were conducted. The values of the variance inflation factor (VIF; Table 4.6) and the condition index (Table 4.7) are acceptable. In addition, the Durbin-Watson test (model summary in Table 4.6) revealed no auto-correlation and no heteroscedasticity, as the null hypothesis of homoscedasticity is not rejected due to the p-value of 0.38 > 0.05 (Table 4.8).

Table 4.6 Output of regression analysis using the logarithm of the annual salary and tacit and explicit skills (Models 3 and 4)

		Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics
Model 3		B	Std. Error	Beta	t	Sig.	VIF
1	(Constant)	3.598	.119		30.131	<.001	
	Eaverage	.043	.020	.199	2.132	.040	1.077
	Taverage	.174	.021	.777	8.348	<.001	1.077

Model summary: R^2(adj. R^2)= .726(.710), F= 45.096 Durbin-Watson (2.028)	$Log(Y_{Salary}) = \beta_0 + \beta_1 X_{Eaverage} + \beta_2 X_{Taverage} + \varepsilon$

a. Dependent Variable: COMPUTE Log10salary=LG10(annualmean2018may)

Model 4		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	3.683	.118		31.162	<.001
	Taverage	.186	.021	.830	8.818	<.001
Model summary: R^2(adj. R^2)= .690(.681), F= 77.764				$Log(Y_{Salary}) = \beta_0 + \beta_1 X_{Taverage} + \varepsilon$		

a. Dependent Variable: COMPUTE Log10salary=LG10(annualmean2018may)

Table 4.7 Collinearity statistics-conditions index

Model 3	Dimension	Eigenvalue	Condition Index
1	1	2.941	1.000
	2	.045	8.093
	3	.014	14.454

Table 4.8 Breusch-Pagan test for heteroscedasticity

Chi-Square	df	Sig.
.770	1	.380

a. Dependent variable: COMPUTE Log10salary=LG10(annualmean2018may)

b. Tests the null hypothesis that the variance of the errors does not depend on the values of the independent variables

c. Predicted values from design: Intercept + Eaverage + Taverage

The regression results efficiently summarize the final observation from the analysis in this study, supporting the findings of the analysis using qualitative research methods.

To answer RQ3 of this study (How can skill-element significance be used to predict how technology advancement impacts salary and productivity?), the observations made in the preceding subsections need to be interpreted. Section 4.4 discussed how classifications regarding job zones, formal education level, and skill category do not help explain the skill changes observed. Due to this lack of classification of the observed skill changes with standard means, a classification regarding tacit and explicit skills was proposed. The classification revealed tacit and explicit skills can explain other factors (e.g., salary) in employment. In particular, this analysis demonstrates the salaries of occupations can be explained by changes in skill elements classified according to tacit and explicit knowledge.

4.6.2 Use of tacit and explicit knowledge classification in economic models

Regarding the production function, previous studies have discussed employment changes due to technological change by changing the inputs for production for the same output (Acemoglu & Restrepo, 2018b; Autor et al., 2003; Frey & Osborne, 2017). The constant elasticity substitution (CES) model has been used to discuss the relative demand for workers with different levels of education for production tasks due to the introduction of technology. The CES model usually calculates the implied change in demand for college graduates and high school graduates based on observed changes in employment and earnings (Autor et al., 2003). In previous studies, the CES model has also been used to explain changes in demand for educated workers (e.g., college graduates) due to changes in tasks resulting from technological change. For example, the introduction of computer technology increased the employment of college graduates and tended to favor more educated workers (Autor et al., 2003; Spitz-Oener, 2006).

However, advances in technology threaten a much broader range of jobs than those that computers have been able to replace. In particular, Acemoglu and Restrepo (2018b) discuss how the automation corresponding to each skill group affects the wages of that group (i.e., automation for low-skilled tasks affects low-skilled workers, and automation for high-skill tasks affects high-skilled workers), stating that even occupations requiring a high level of education are not safe from changes in wages or employment conditions.

Therefore, information about the significance of skill elements or the changes in their significance could be highly valuable for other economic models, such as production functions (Autor et al., 2020; Goldin & Katz, 2007). In previous studies, the model describes aggregate output with two input factors: the number of skilled workers and the number of unskilled workers. These numbers of skilled and unskilled laborers are determined based on having or not having a college education (Autor et al., 2020; Goldin & Katz, 2007).

Based on the results of this study, the CES model in previous studies (Autor et al., 2020; Goldin & Katz, 2007) could be extended by replacing formal education with skills in their model. For example, the conceptual model, based on the one of Autor, Goldin, and Katz

(2020), could look as follows: on output Q, with the two factors of tacit skill of labor (L_T) and explicit skill of labor (L_E), which are used for performing tasks within an occupation:

$$Q_t = \left[\alpha_t\left(a_t L_{T_t}\right)^{\rho} + (1-\alpha_t)\left(b_t L_{E_t}\right)^{\rho}\right]^{\frac{1}{\rho}}$$

where L_T represents the tacit skill of labor and L_E the explicit skill of labor used to perform tasks in period t. The variables α_t and b_t represent technological change for labor, and α_t is a time-varying technology parameter that can be indexed to the share of tasks utilizing tacit skills of labor. The production parameter ρ is $\sigma_{TE} = 1/(1-\rho)$, according to Autor, Goldin, and Katz (2020).

With the proposed production function, it would be possible to compare occupations within the same education group. Moreover, this approach can help to understand changes of skills in occupations over time. For example, the ratio of tacit skills (L_T) and explicit skills of labor (L_E) might change in the same occupation over time.

4.6.3 Discussion of results

The results reveal that, to determine the relative demand for workers in the production of output, it is necessary to use the skills workers actually utilize to perform tasks as factors considered in production, not the size of employment or wages by education level.

Regarding RQ3 (How can skill-element significance be used to predict how technological advancement impacts salary and productivity?), classifying skills as tacit and explicit was proposed. This proposal stemmed from the discussion that the classification of skills by skill category or level of formal education did not help to explain the observations stated in the existing research. When this classification was examined with the analysis result of skill changes, it was found that skill changes with increased significance were more tacit, and skill changes with decreased significance were more explicit (Figure 4.10).

In addition, the relationship of tacit and explicit skills to salary was studied to check whether the classification of skills based on tacit and explicit knowledge can explain other factors in employment. This analysis revealed the salaries of occupations can be explained by changes in skill elements classified as tacit and explicit. Following these positive results, it was discussed how tacit and explicit skill classifications can be used in labor productivity analysis to explain labor demand in the production function of the economic model.

Overall, through this study, it revealed it is important to understand the significance of skill elements and their changes over time. The results in Sections 4.6.1 and 4.6.2 demonstrate the applicability of tacit and explicit skills as input for predicting economic variables in other economic models. The proposed approach to classifying skills can explain skill changes and skill significance and be used to predict and account for salary and productivity. It is expected that tacit and explicit skills could also be useful in explaining other phenomena. For example, Autor et al. (2020) state that an explanation is needed for their observation regarding the polarization of wages for occupations within the same level of formal education.

4.7 Conclusions

4.7.1 Summary of major findings

This study analyzed existing skills and identified significant skill changes. Information about occupations was collected from the O*NET database for 37 occupations in 2003 and 2018. The skills of the collected occupations were examined regarding their significance. First, skills in different groupings of occupations were explored. Changes in significance for skills in occupations were analyzed between 2003 and 2018, confirming the significance of almost all skills changed in occupations over time. Moreover, skill significance varied for every occupation and skill element (Column 1 of Table 4.9). Even for occupations in the same job group categorized by similar levels of working experience and education, the change in significance for every skill element differed (Column 2 of Table 4.9). The only common finding was that the skill category of social skills became more significant, but the skill category of technical skills became less significant in 2018. Second, skills were examined for their changes across occupations over time to figure out which became more significant. The significance of 20 skills out of 35 increased in 2018. Among these skills, negotiation was the most significant skill, with the biggest changes on average, followed by persuasion (Column 3 of Table 4.9).

Based on the findings regarding skill changes, skills were classified to capture skill changes and provide a proper approach to explain skill changes in a model. Skill elements were classified into tacit and explicit, based on Polanyi (1966) and Spitz-Oener (2006). All 35 skills were examined, and 24 were identified as tacit and 11 as explicit. Reviewing the skill changes observed across occupations confirmed that most of the skills that changed positively over time were tacit skills. However, many explicit skills decreased in 2018 (Column 4 of Table 4.9). Furthermore, the average level of significance for tacit and explicit skills was presented, in addition to the annual mean salary from 2018. The scatter diagram revealed a linear relationship between tacit skills and salary. The average of tacit skills increased as salary increased, but the scatter diagram for explicit skills revealed it was difficult to state there was a relationship between explicit skills and salary. The regression analysis also revealed a linear relationship between salary and the two types of skills. This simple result demonstrated that describing occupations by sharing tacit and explicit knowledge types can provide an appropriate framework to explain skill changes understood through qualitative research with other factors in the labor market.

Table 4.9 Summary of findings

	Section 4.4.1	**Section 4.4.2**	**Section 4.4.3**	**Section 4.5**
Data	Change in skill significance for each skill	Average value by group for skill significance for each skill	Change in skill significance for each skill and the average value of each skill across all occupations	Skill definitions from the O*NET and change in skill significance for each skill and the average value of each skill across all occupations

Result analysis	Examining how skill changed over time within occupations	Examining how skill changed over time based on education level	Identifying which skill changed significantly over time	Identifying knowledge types of skills changed over time
Results presentation	By job zones	By education level	By skill category	By tacit and explicit knowledge
Major finding	- Every skill was considered differently over time for all occupations - In general, the significance of skills in the category of social skills increased, whereas the significance of skills in the category of technical	- Skill changes were greater for occupations with a low education level than for those with a high education level - Both groups displayed increasing significance in the category of social skills but decreasing	- The average skill significance of 20 out of 35 skill elements increased, whereas 15 out of 35 skill elements decreased - The skill with the largest increase in significance was negotiation, and the skill with the largest decrease in	- Of the 35 skills, 24 had aspects of tacit knowledge, and 11 had aspects of explicit knowledge - Of the 20 skills that increased in average significance, 18 were based on tacit knowledge, and nine of the 15 skills that decreased in average significance were based on explicit knowledge

skills decreased	significance in the category of technical skills	significance was equipment selection

4.7.2 Contributions

This study contributes to our understanding of how the significance of skills changed over time. Some skills became more significant over time, but others became less significant as skills were required differently. Moreover, workers recognized the different skills required to perform tasks in each occupation based on their needs, and they changed and improved their skills accordingly and continuously. Specifically, social skills were emphasized, whereas technical skills were less valued. This result, regarding the importance of social skills, is in line with a few studies discussing social skills, such as Deming (2017) and Sadun et al. (2022).

A key feature of these skill changes is that they occurred across occupations and worker education levels. All the skills changed over time, and the changes in skills that are difficult for machines to perform, such as negotiation and persuasion, are more pronounced. These skill changes are difficult to understand using the traditional approach of explaining workers' skills by their education level. Moreover, the skills workers use to perform tasks could not be differentiated by quantitative analysis.

To measure workers' skills that cannot be explained by their education level, this study conducted a qualitative analysis of skills and divided them based on tacit and explicit knowledge. This classification ensures the labor inputs used in the existing model of relative demand for workers actually account for worker skill. This point illustrates the implications of this study's findings through qualitative analysis. In particular, this study is consistent with the existing literature that quantitative approaches have limitations as the number of workers shrinks and qualitative research becomes more important (Pfeiffer, 2018).

Overall, and most important, this study presented more details about labor skills compared with previous studies. Specifically, formal education level is insufficient to describe skills. Furthermore, the results could help to generate new models for predicting salary and for extensions of well-known production models, such as the one of Goldin and Katz (2007). The analysis results and the classification proposed can provide a chance to observe labor productivity with skills other than formal education and to compare differences in labor productivity within the same education level.

For example, when explaining wage inequality within the same level of education, the relationship between tacit and explicit skills and the average wage level for each occupation is evident. In addition, by understanding the change in the two types of skills used in each occupation, the flow of the change in wages can be examined. The results of this study suggest that, by defining skills according to the relevant knowledge type, technological change can be more directly reflected in the change in a worker’s skills, and the two type of skills defined can be used as a variable to observe the change in worker’s skills due to technological change at the individual level. These variables describe the skills of workers performing tasks within an occupation, and thus, they can account for changes in tasks in an occupation associated with changes in skills, as well as the changes in the occupation the changed tasks constitute.

Even if skills are defined as tacit and explicit according to knowledge type and used as variables, this still cannot comprehensively explain changes in technology and skills related to factors such as wages in the labor market. In addition, to use a variable continuously, full observation for skills and changes in skills should be steadily reflected in the variable so it can be properly analyzed and interpreted at that point. The nature of these variables is also important because the purpose of presenting them is to reflect changes in skill that are relevant at the moment and to fill the gaps that cannot be explained by existing skill-related variables.

4.7.3 Limitations

This study performed a rigorous analysis but could not avoid a few limitations. First, the types of occupations from the collected data were not evenly distributed due to the limited data available that fulfilled the defined conditions of this study for the two years of 2003 and 2018. Therefore, if more technology and engineering-related occupations were included, technical skills might be found to be more valuable than the current results suggest. Second, this study's research method focused on a qualitative approach to skills using secondary data. One purpose of this study was to observe changes in skills that could not be captured by education, so a qualitative approach was chosen to engage different perspectives from previous studies. Thus, this study could not describe any causal relationships statistically, such as wages and skills, or employment and skills. In the future, the research could be extended by increasing the number of occupations analyzed (but with different selection criteria applied) and using data from other countries.

Chapter 5. Conclusions

5.1 Overall discussion

In this thesis, the impact of technological changes on work and service was studied using qualitative research methods to describe the relationships between work, service, and technological changes and to provide a framework to explain technological changes in work and service. By revisiting existing research and its approaches, this thesis emphasized seemingly inconspicuous details. First, the research identified new characteristics in services that appeared due to technological development. These characteristics were significant enough, for instance, in emerging services, such as platform services, to disrupt the industry and cause problems in the existing system, but they have rarely been reviewed regarding their reflection in the system. If technology can change the shape of an industry, it can be assumed it has also affected related factors within the industry, such as workers, tasks, and skills. Second, this thesis identified changes in skills at work according to technological changes. Skills are required to perform the tasks of an occupation, so it is necessary to consider how workers respond to different tasks and change working environments; for example, by using new machines, software programs, and devices. Nonetheless, changes in the skills of workers have received little attention. Even when skills have been examined, they were mostly measured using one piece of information: formal education. However, because some skills are difficult to measure through formal education, there is a limitation to describing how technology impacts skills. Technological changes are interrelated (Dolata, 2009, 2013), and transformations occur collectively through cooperation between actors in organizations (Dosi & Virgillito, 2019). To understand the impact of technology as a whole, observing and disclosing unnoticed details is important. These details were studied throughout this thesis to complement and advance the current frameworks.

Therefore, a qualitative research approach was employed to address the research questions: 1) How are services impacted by technological changes? 2) How do tasks and skills respond to technological changes, and how can changes in tasks and skills be explained? 3) How can skill changes be described and captured in an analytical framework? Based on observations and findings, answers were provided by taking the opportunity to understand circumstances, address problems, and build a theoretical framework (Bryman, 2012; Yin, 2014). In this thesis, three studies were presented focusing each research question. First, service classification was studied as a system of defining and categorizing services. Service was specifically focused on to consider new services appearing and spreading rapidly with information technology, such as a business based on a platform. A systematic literature review was conducted, followed by a rigorous procedure for analyzing existing service classifications, from which common attributes for considering customers and managing processes were found. These attributes were applied to discuss whether existing attributes of service classification could cover emerging services, such as platform-based businesses like TaskRabbit. The attributes of the existing classification were insufficient to describe platform services thoroughly. Mainly, the attributes could not address changes for new businesses and transformed processes caused by technology. To resolve these shortcomings, three new attribute dimensions were proposed for a comprehensive classification. The first attribute dimension, ‘degree of involvement,’ was used to express the quality of interaction and the type of information exchanged between the involved actors. The second attribute dimension, ‘degree of competency,’ was determined from the notion that knowing how to use a device is a form of competency of skills and knowledge (Vargo & Lusch, 2004, 2008). In other words, some people are more likely to join a platform if they are familiar with digital devices. The third attribute dimension, ‘service scene,’ addresses a sequence of continuous actions in the service process that can occur in the virtual world, real world, or a combination of both.

As much as technology can change the shape of industries, this alteration also affects the people who work in them. Accordingly, the description for technological changes should be improved by considering related factors. Hence, the second analysis concerned technological changes at work. A case study of one occupation, cashier, was conducted to understand the transformation of tasks and skills. The findings confirmed that cashier tasks have changed steadily, as have the skills required over time. The tasks and skills have transformed together. A certain tendency was identified regarding making tasks that are difficult to codify more significant. With changes in tasks, different skills were found to be important and required, and cognitive and social skills were emphasized. Moreover, both tasks and skills involve communication and interpersonal features, which are too implicit to express in software and hardware or could still be too expensive to operate by machines.

As a result, cashiers responded to changes by emphasizing relevant skills, such as social skills, and reducing less useful skills, such as technical skills, for the job. Concentrating on one occupation allowed for understanding the changes that occurred within it in depth.

Based on the findings from this second analysis, the third analysis was set. In this analysis, the skills required to perform tasks were analyzed further. Skill changes within and across occupations were investigated to understand how skills have changed over time and in which framework skill changes can be presented. Thirty-seven occupations from different occupational groups were examined, and the skills required for these occupations were observed in several steps. First, it was confirmed that the significance of almost all skills has changed in occupations over time. However, the significance of those skills changed differently for every occupation and skill element. In general, social skills were considered more important, and this category revealed positive changes on average for all occupations. On the other hand, technical skills were generally considered less important over time, and the category revealed negative changes on average for all occupations. Second, changes in skills in occupations were examined at the formal education level. Changes in skills in occupations of the low formal-education group were greater than in the high formal-education group. This result demonstrated the same tendency of social skills becoming more important and technical skills becoming less important over time for both formal education groups. The category of social skills changed more positively in occupations of the low education group than in the high education group, and the category of technical skills changed more negatively in occupations of the high education group than in the low education group. Third, changes in skills were examined for all 35 skill elements, with seven skill categories across all 37 occupations, to determine the skills that changed the most. The changes in skills in the category of social skills for all occupations were significant, and two skills, negotiation and persuasion, became much more meaningful over time Fourth, all the skill elements were identified and classified into two types of knowledge, tacit and explicit, to explore changes in skills based on their characteristics and to address the limitations of conventional methods of defining skills. This study attempted to capture skill changes and to explain skill changes in a model. Most skills that increased in significance over time included aspects of tacit knowledge, and those skills that decreased in significance over time included more aspects of explicit knowledge. Furthermore, the average level of significance for tacit and explicit skills was presented in addition to the annual mean salary in 2018. The scatter diagrams illustrated a linear relationship between tacit skills and salary, but a clear correlation between explicit skills and salary was not found. Regression analysis using the logarithm of the 2018 salary revealed a linear relationship between two types of skills and salary. This result demonstrates that describing occupations by the shares of tacit and explicit knowledge types can be significant for explaining skill changes with other factors in the labor market and be an appropriate framework to explain skill changes.

5.2 Implications of the results

This thesis began by suggesting the importance of studying the transformation caused by technological development from a different point of view. For example, when technology can change the shape of industries with new services and products, its impacts should be related to people and institutions, and when technology can replace or displace tasks in occupations, the responses of workers to changes should be considered. Technological changes occur as a continuous and dynamic process by relating various factors within a socio-economic system. Therefore, this thesis focused on small but related factors using a qualitative research approach. This method could be an unexpected approach, especially since major research on the topic has utilized quantitative methods. Therefore, this thesis is meaningful and necessary to broaden the perspective by revising existing approaches to constant technological development. This broadening was achieved by studying technological changes at work and in systems to learn how these respond to technological changes and how changes in them can be explained. The findings of this study revealed the undertaking was worthwhile.

5.2.1 Understanding services through service classification

Analyzing the attributes of existing services addressed the limitations of understanding services. The systematic literature review found most similarities in existing service classifications and their attributes regarding considering customers and managing processes. It was obvious that two, considering customer and managing process were important in service, but the main issue was that technology has greatly affected customer and process in service. Applying existing attributes to the case of platform services determined that traditional attributes were insufficient to explain the case. Existing service classifications failed to explain current transitions from traditional services to pure online services (e.g., video rental shop to online streaming service) caused by technological developments. To understand emerging services, such as platform-based services, it is necessary to have an appropriate service classification scheme. A few attempts were made to develop such a scheme, including digital platform classification (Schmidt, 2017), was also useful for classifying platform businesses. To ensure digital platforms comply with the present legal systems, this study chose to extend the existing classifications. The extension needed to consider both emerging services based on both innovation and traditional services, which still comprise an enormous portion of the economy. The approach of classifying service in this study will enable platforms to adapt and take actions now before there is a need to transform the entire system. Therefore, three additional attributes focusing on the shortcomings of existing service classifications were proposed to cover emerging platform services by complementing existing classifications. This suggested consolidated service classification can, to some extent, provide an understanding of services in the context of technology development.

5.2.2 Evolving skills and tasks

When industries adopt new technology, they need to consider the workers, who are also impacted. There are many examples of technology being introduced in the workplace, such as computers and software in offices, automated teller machines, mobile banking in financial services, and self-checkout stands at stores. These examples have changed the tasks performed by workers in occupations, and researchers have discussed tasks as a result of computerization and automation and their effects (e.g., Arntz et al., 2017; Autor et al., 2003; Frey and Osborne, 2017; Spitz-Oener, 2006). Moreover, skills are required to perform tasks. When new technology is introduced, a learning process begins, and new technology initiates changes in the skills of workers (Arrow, 1962). The results of a case study of cashiers revealed that skills have changed in line with the tasks in the occupation. Furthermore, the results confirmed that tasks that are difficult to codify became more significant, especially cognitive and social tasks. The possibility of technological changes might trigger new and more complex tasks that can be performed better by workers, as indicated in previous studies (i.e., Acemoglu and Restrepo, 2018c; Autor, 2015; Bessen, 2015). Studying one occupation (cashiers) in depth confirmed that changes occurred in the occupation regarding the skills in which workers held a comparative advantage. Major tasks were found to require interactive and social elements, which are too complicated to be automated for now. Furthermore, with changes in tasks, different skills were found to be important and required. Cashiers responded to changes by emphasizing more relevant skills (i.e., social skills) and reducing less useful skills (i.e., technical skills). However, it could not be determined whether cashiers responded to technological changes actively or passively, but this study revealed that workers were aware of changes regarding their job and chose to develop and improve their advantages. This study also confirmed that a qualitative approach using descriptive data is beneficial and meaningful to analyze the relationship between technological changes and work. The research methodology uncovered details and relationships that were not obvious from statistical analysis and that could fill small gaps by complementing an aggregate level of economic research.

5.2.3 Extending the understanding of technological changes

The occupation of cashiers transformed to respond to external changes. This result implies that changes in skills and tasks in an occupation occur simultaneously. Furthermore, this observation was extended to other occupations to obtain an understanding of changes in skills within and across occupations. Skills were required differently across occupations and occupational group categories according to similar levels of education, training, and experience. Workers recognized skills differently, performed tasks in each occupation based on their needs, and changed and improved their skills continuously. Nevertheless, it was expected that social skills would be recognized much more than other skills. Social skills were emphasized several times throughout this study, as were the results from other studies, such as Deming (2017) and Sadun et al. (2022). Deming's (2017) findings express the importance of social skills in performing tasks and working with colleagues. However, looking at the variables for social skills defined in that study, defined social skills based on sociability or measured them with four social elements of coordination, negotiation, persuasion, and social perceptiveness from the O*NET, that study's view for social skills is limited to teams. Sadun et al. (2022) discuss social skills as being critical to leaders at the executive level or other senior managers and to technology-intensive firms, but their discussion largely focuses on explaining the importance of social skills generally from a managerial perspective. The results of this present thesis support these mentioned studies by outlining the importance of social skills and providing greater details about two social skills, negotiation and persuasion, that were expected to be valuable for working with others. Observations using a qualitative approach offered detailed characteristics of skills in terms of skill changes within and across occupations. However, workers' skills regarding their abilities to perform tasks (e.g., social skills) could not be fully explained using formal education levels typically used to measure skills. This difficulty was also highlighted when evaluating social skills in the process of employment (Sadun et al., 2022).

Traditionally, in the labor market, workers' skills have been measured by their level of formal education. A worker with a high level of education (i.e., college or higher education) has been considered one whose productivity is high. In this way, the education certificate worked as a signal in the labor market that the worker holding a higher education degree can be more productive and deserves higher earnings (Borjas, 2020). This study revealed the traditional measures have limitations in explaining skills and skill changes. To explain the skill changes observed in this study and to capture their changes in a different model, skills were classified into tacit and explicit skills according to their relevant knowledge types. Occupations were described by shares of tacit and explicit, and their changes in skills were reviewed. The findings verified that classifying skills according to their knowledge type could explain other factors in the labor market. These results could enable the extending of well-known production functions, such as those of Autor et al. (2020) and

Goldin and Katz (2007), by providing a different perspective to explain skills and their changes. This approach could be an opportunity to observe labor productivity with skills other than formal education and to review workers' productivity at the same education level.

5.3 Directions for future research

The results of this thesis revealed the effectiveness of qualitative analyses in putting details into perspective. Technological changes occur simultaneously, affecting all major and minor actors and events. Based on the findings, there are directions for future research. First, regarding data availability, the O*NET database is highly useful and widely employed in research; however, it was established and is based in the US, so it may not reflect other conditions. There are many differences between countries in terms of labor markets, economic developments, technological innovations, and other factors. Therefore, it would be beneficial to build a dataset for other countries as well. Second, the types of occupations from the collected data were not evenly distributed when studying skills across occupations due to data availability. Further research could include more occupations and other countries in other databases. Third, the analysis assumed that technological changes underlie the overall working environment. Therefore, any direct causality or correlation between displacing machines and workers was not intended to be proven. Consequently, an interesting direction for future work would be investigating skill changes to understand the correlations between workers and machine introduction in depth.

Bibliography

Abraham, K. G., & Mallatt, J. (2022). Measuring Human Capital. *Journal of Economic Perspectives, 36*(3), 103-130. doi:10.1257/jep.36.3.103

Acemoglu, D., & Restrepo, P. (2017). *Robots and Jobs: Evidence from US Labor Markets*. Retrieved from http://www.nber.org/papers/w23285

Acemoglu, D., & Restrepo, P. (2018a). *Artificial Intelligence, Automation and Work*. Retrieved from https://www.nber.org/papers/w24196

Acemoglu, D., & Restrepo, P. (2018b). Low-skill and high-skill automation. *Journal of Human Capital, 12*(2), 204-232. doi:10.1086/697242

Acemoglu, D., & Restrepo, P. (2018c). The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment. *American Economic Review, 108*(6), 1488-1542. doi:10.1257/aer.20160696

Adams, A., Freedman, J., & Prassl, J. (2018). Rethinking legal taxonomies for the gig economy. *Oxford Review of Economic Policy, 34*(3), 475-494.

Alabdulkareem, A., Frank, M. R., Sun, L., AlShebli, B., Hidalgo, C., & Rahwan, I. (2018). Unpacking the polarization of workplace skills. *Science advances, 4*(7), eaao6030.

Altmann, J., Meschke, M., & Bany, A. (2012). A Classification Scheme for Characterizing Service Networks. *TEMEP Discussion Papers, 201286*.

Arntz, M., Gregory, T., & Zierahn, U. (2017). Revisiting the risk of automation. *Economics Letters, 159*, 157-160.

Arrow, K. J. (1962). The Economic Implications of Learning by Doing. *The Review of*

Economic Studies, 29(3), 155-173.

Atalay, E., Phongthiengtham, P., Sotelo, S., & Tannenbaum, D. (2020). The evolution of work in the United States. *American Economic Journal: Applied Economics, 12*(2), 1-34.

Atkinson, A. B., & Stiglitz, J. E. (1969). A New View of Technological Change. *The economic journal, 79*(315), 573-578. doi:10.2307/2230384

Autor, D. H. (2015). Why are there still so many jobs? The history and future of workplace automation. *Journal of Economic Perspectives, 29*(3), 3-30.

Autor, D. H. (2022). *The Labor Market Impacts of Technological Change: From Unbridled Enthusiasm to Qualified Optimism to Vast Uncertainty*. Retrieved from http://www.nber.org/papers/w30074

Autor, D. H., & Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the US labor market. *American Economic Review, 103*(5), 1553-1597.

Autor, D. H., Goldin, C., & Katz, L. F. (2020). Extending the Race between Education and Technology. *AEA Papers and Proceedings, 110*, 347-351. doi:10.1257/pandp.20201061

Autor, D. H., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics, 118*(4), 1279-1333.

Barnes, D. C., Collier, J. E., Ponder, N., & Williams, Z. (2013). Investigating the employee's perspective of customer delight. *Journal of Personal Selling & Sales*

Management, 33(1), 91-104.

Barnes, D. C., Ponder, N., & Hopkins, C. D. (2015). The impact of perceived customer delight on the frontline employee. *Journal of Business Research, 68*(2), 433-441.

Bessen, J. (2015). Toil and Technology. *Finance & Development, 52*(1), 16-19. Retrieved from http://www.imf.org/external/pubs/ft/fandd/2015/03/bessen.htm

Bitner, M. J. (1992). Servicescapes: The impact of physical surroundings on customers and employees. *The Journal of Marketing*, 57-71.

Bitner, M. J., Booms, B. H., & Tetreault, M. S. (1990). The service encounter: diagnosing favorable and unfavorable incidents. *The Journal of Marketing*, 71-84.

Bittarello, L., Kramarz, F., & Maitre, A. (2018). The Task Content of Occupations. *Discussion Paper Seires,* (DP No.12006). Retrieved from https://www.iza.org/pub/6UvHs9sg

Borjas, G. J. (2020). *Labor economics* (8th ed.. ed.). New York: New York : McGraw-Hill Education.

Bowen, J. (1990). Development of a taxonomy of services to gain strategic marketing insights. *Journal of the Academy of marketing science, 18*(1), 43-49.

Boyd, R., & Holton, R. J. (2018). Technology, innovation, employment and power: Does robotics and artificial intelligence really mean social transformation? *Journal of Sociology, 54*(3), 331-345.

Bryman, A. (2012). *Social Research Methods* (4th ed.): Oxford University Press.

Bureau of Labor Statistics. (2018, September 4, 2019). Occupational Outlook Handbook, Cashiers. Retrieved from https://www.bls.gov/ooh/sales/cashiers.htm

Buzacott, J. A. (2000). Service system structure. *International Journal of Production Economics, 68*(1), 15-27.

Carlborg, P., & Kindström, D. (2014). Service process modularization and modular strategies. *Journal of Business & Industrial Marketing, 29*(4), 313-323.

Chase, R. B. (1978). Where does the customer fit in a service operation? *Harvard business review, 56*(6), 137-142.

Chase, R. B. (1981). The customer contact approach to services: theoretical bases and practical extensions. *Operations research, 29*(4), 698-706.

Chase, R. B., & Tansik, D. A. (1983). The customer contact model for organization design. *Management Science, 29*(9), 1037-1050.

Choudary, S. P., Van Alstyne, M. W., & Parker, G. G. (2016). *Platform revolution: How networked markets are transforming the economy--and how to make them work for you*: WW Norton & Company.

Cirillo, V., Rinaldini, M., Staccioli, J., & Virgillito, M. E. (2021). Technology vs. workers: the case of Italy's Industry 4.0 factories. *Structural Change and Economic Dynamics, 56*, 166-183.

Cook, D. P., Goh, C. H., & Chung, C. H. (1999). Service typologies: a state of the art survey. *Production and Operations Management, 8*(3), 318-338.

Cunningham, L. F., Young, C. E., & Gerlach, J. H. (2008). Consumer views of self-service technologies. *The Service Industries Journal, 28*(6), 719-732.

Cunningham, L. F., Young, C. E., & Lee, M. (2005). Customer perceptions of service dimensions: American and Asian perspectives. *The Service Industries Journal, 25*(1), 43-59.

Cunningham, L. F., Young, C. E., Lee, M., & Ulaga, W. (2006). Customer perceptions of service dimensions: cross-cultural analysis and perspective. *International Marketing Review, 23*(2), 192-210.

Cunningham, L. F., Young, C. E., Ulaga, W., & Lee, M. (2004). Consumer views of service classifications in the USA and France. *Journal of Services Marketing, 18*(6), 421-432.

Cusumano, M. A., Kahl, S. J., & Suarez, F. F. (2015). Services, industry evolution, and the competitive strategies of product firms. *Strategic management journal, 36*(4), 559-575.

Dalziel, M. (2007). A systems-based approach to industry classification. *Research Policy, 36*(10), 1559-1574. doi:https://doi.org/10.1016/j.respol.2007.06.008

David, A. H. (2014). A service sector classification scheme using economic data. *The Service Industries Journal, 34*(4), 335-353.

Deming, D. J. (2017). The growing importance of social skills in the labor market. *The Quarterly Journal of Economics, 132*(4), 1593-1640.

Deming, D. J. (2022). Four Facts about Human Capital. *Journal of Economic Perspectives, 36*(3), 75-102. doi:10.1257/jep.36.3.75

Dengler, K., & Matthes, B. (2018). The impacts of digital transformation on the labour market: Substitution potentials of occupations in Germany. *Technological Forecasting and Social Change, 137*, 304-316.

Dolata, U. (2009). Technological innovations and sectoral change: Transformative capacity, adaptability, patterns of change: An analytical framework. *Research Policy, 38*(6), 1066-1076. doi:10.1016/j.respol.2009.03.006

Dolata, U. (2013). *The transformative capacity of new technologies: A theory of sociotechnical change* (1st ed.): Routledge.

Dolata, U. (2018). *Technological Innovations and the Transformation of Economic Sectors. A Concise Overview of Issues and Concepts*. Retrieved from https://www.sowi.uni-stuttgart.de/dokumente/forschung/soi/soi_2018_1_Dolata.Technological.innovations.transformation.economic.sectors.pdf

Donthu, N., Kumar, S., Mukherjee, D., Pandey, N., & Lim, W. M. (2021). How to conduct a bibliometric analysis: An overview and guidelines. *Journal of Business Research, 133*, 285-296.

Dosi, G. (1982). Technological paradigms and technological trajectories: a suggested interpretation of the determinants and directions of technical change. *Research Policy, 11*(3), 147-162.

Dosi, G., & Virgillito, M. E. (2019). Whither the evolution of the contemporary social fabric? New technologies and old socio-economic trends. *International Labour Review, 158*(4), 593-625.

Edvardsson, B. (1997). Quality in new service development: Key concepts and a frame of reference. *International Journal of Production Economics, 52*(1-2), 31-46. doi:10.1016/s0925-5273(97)80765-7

Edvardsson, B., Gustafsson, A., & Roos, I. (2005). Service portraits in service research: a critical review. *International Journal of Service Industry Management, 16*(1), 107-121. doi:10.1108/09564230510587177

Farber, H. S. (2017). Employment, Hours, and Earnings Consequences of Job Loss: US Evidence from the Displaced Workers Survey. *Journal of labor economics, 35*, S235-S272. doi:10.1086/692353

Fernández-Macías, E., & Bisello, M. (2022). A Comprehensive Taxonomy of Tasks for Assessing the Impact of New Technologies on Work. *Social Indicators Research, 159*(2), 821-841. doi:10.1007/s11205-021-02768-7

Fisk, R. P., Brown, S. W., & Bitner, M. J. (1993). Tracking the evolution of the services marketing literature. *Journal of retailing, 69*(1), 61-103.

Frey, C. B., & Osborne, M. A. (2017). The future of employment: how susceptible are jobs to computerisation? *Technological Forecasting and Social Change, 114*, 254-280.

Gadrey, J. (2000). The characterization of goods and services: an alternative approach. *Review of income and wealth, 46*(3), 369-387.

Gallouj, F. (1997). Towards a neo-Schumpeterian theory of innovation in services? *Science and Public Policy, 24*(6), 405-420.

Geels, F. W. (2002). Technological transitions as evolutionary reconfiguration processes: a multi-level perspective and a case-study. *Research Policy, 31*(8), 1257-1274.

doi:https://doi.org/10.1016/S0048-7333(02)00062-8

Geels, F. W. (2004). From sectoral systems of innovation to socio-technical systems: Insights about dynamics and change from sociology and institutional theory. *Research Policy, 33*(6), 897-920.

Geels, F. W., & Schot, J. (2007). Typology of sociotechnical transition pathways. *Research Policy, 36*(3), 399-417.

Glückler, J., & Hammer, I. (2011). A pragmatic service typology: capturing the distinctive dynamics of services in time and space. *The Service Industries Journal, 31*(6), 941-957.

Goldin, C., & Katz, L. F. (2007). Long-run changes in the US wage structure: Narrowing, widening, polarizing. In: National Bureau of Economic Research Cambridge, Mass., USA.

Goos, M., & Manning, A. (2007). Lousy and lovely jobs: The rising polarization of work in Britain. *The Review of Economics and Statistics, 89*(1), 118-133.

Goos, M., Manning, A., & Salomons, A. (2009). Job polarization in Europe. *American Economic Review, 99*(2), 58-63.

Goos, M., Manning, A., & Salomons, A. (2014). Explaining job polarization: Routine-biased technological change and offshoring. *American Economic Review, 104*(8), 2509-2526.

Grönroos, C. (1988). Service quality: The six criteria of good perceived service. *Review of business, 9*(3), 10.

Gummesson, E. (2000). Services Marketing Self-Portraits: Introspections, Reflections, and Glimpses from the Experts. In R. P. Fisk, S. J. Grove, & J. John (Eds.), (pp. 109-132): American Marketing Association.

Hadden, W. C., Kravets, N., & Muntaner, C. (2004). Descriptive dimensions of US occupations with data from the O* NET. *Social Science Research, 33*(1), 64-78.

Haile, N., & Altmann, J. (2016a). Structural analysis of value creation in software service platforms. *Electronic Markets, 26*(2), 129-142.

Haile, N., & Altmann, J. (2016b). Value creation in software service platforms. *Future Generation computer systems, 55*, 495-509.

Haywood-Farmer, J. (1988). A conceptual model of service quality. *International Journal of Operations & Production Management, 8*(6), 19-29.

He, Q., Ghobadian, A., Gallear, D., Beh, L.-S., & O'Regan, N. (2016). Towards conceptualizing reverse service supply chains. *Supply Chain Management: An International Journal, 21*(2), 166-179.

Henneberg, S. C., Gruber, T., & Naudé, P. (2013). Services networks: Concept and research agenda. *Industrial Marketing Management, 42*(1), 3-8.

Hershbein, B., & Kahn, L. B. (2018). Do Recessions Accelerate Routine-Biased Technological Change? Evidence from Vacancy Postings. *The American Economic Review, 108*(7), 1737-1772. Retrieved from https://www.jstor.org/stable/26528520

Hicks, D. (2011). Structural change and industrial classification. *Structural Change and Economic Dynamics, 22*(2), 93-105.

doi:https://doi.org/10.1016/j.strueco.2011.03.001

Hill, P. (1977). On goods and services. *Review of income and wealth, 23*(4), 315-338.

Hill, P. (1999). Tangibles, intangibles and services: a new taxonomy for the classification of output. *The Canadian journal of economics/Revue canadienne d'Economique, 32*(2), 426-446.

Holmqvist, J., & Grönroos, C. (2012). How does language matter for services? Challenges and propositions for service research. *Journal of Service Research, 15*(4), 430-442.

Isaac, E. (2015). *Innovative Clusters & New Work: A case study of TaskRabbit*: Berkeley Roundtable on the International Economy [University of California, Berkeley].

Jaakkola, E., Meiren, T., Witell, L., Edvardsson, B., Schäfer, A., Reynoso, J., . . . Weitlaner, D. (2017). Does one size fit all? New service development across different types of services. *Journal of Service Management, 28*(2), 329-347.

Johansson, P., & Olhager, J. (2006). Linking product–process matrices for manufacturing and industrial service operations. *International Journal of Production Economics, 104*(2), 615-624.

Judd, R. C. (1964). The case for redefining services. *Journal of marketing, 28*(1), 58-59.

Kelley, S. W., Donnelly, J. H., & Skinner, S. J. (1990). Customer participation in service production and delivery. *Journal of retailing, 66*(3), 315-335.

Kellogg, D. L., & Nie, W. (1995). A framework for strategic service management. *Journal of Operations Management, 13*(4), 323-337.

Kenney, M., & Zysman, J. (2015). *Choosing a future in the platform economy: the* *implications and consequences of digital platforms.* Paper presented at the Kauffman Foundation New Entrepreneurial Growth Conference.

Larsson, R., & Bowen, D. E. (1989). Organization and customer: managing design and coordination of services. *Academy of Management Review, 14*(2), 213-233.

Lee, S., & Park, Y. (2009). The classification and strategic management of services in e-commerce: Development of service taxonomy based on customer perception. *Expert Systems with Applications, 36*(6), 9618-9624.

Lemieux, T. (2006). *The "Mincer Equation" Thirty Years After Schooling, Experience, and Earnings*. Boston, MA: Boston, MA: Springer US.

Liu, C.-H., & Wang, C.-C. (2008). Forecast competitor service strategy with service taxonomy and CI data. *European Journal of Marketing, 42*(7/8), 746-765.

Liu, C.-H., Wang, C.-C., & Lee, Y.-H. (2008). Revisit service classification to construct a customer-oriented integrative service model. *International Journal of Service Industry Management, 19*(5), 639-661.

Lovelock, C. H. (1983). Classifying Services to Gain Strategic Marketing Insights. *The Journal of Marketing, 47*(3), 9-20.

Lovelock, C. H., & Gummesson, E. (2004). Whither services marketing? In search of a new paradigm and fresh perspectives. *Journal of Service Research, 7*(1), 20-41.

Lovelock, C. H., & Patterson, P. (2015). *Services Marketing* (6th ed.): Pearson Australia.

Lucas, C., Nielsen, R. A., Roberts, M. E., Stewart, B. M., Storer, A., & Tingley, D. (2015). Computer-assisted text analysis for comparative politics. *Political Analysis, 23*(2), 254-277.

Maglio, P. P., Srinivasan, S., Kreulen, J. T., & Spohrer, J. (2006). Service systems, service scientists, SSME, and innovation. *Communications of the ACM, 49*(7), 81-85.

Maister, D. H., & Lovelock, C. H. (1982). Managing facilitator services. *Sloan Management Review, 23*(4), 19.

Mariani, M. (1999). Replace with a database: O*NET replaces the Dictionary of Occupational Titles. *Occupational outlook quarterly, 43*, 2-9.

McDermott, C. M., Kang, H.-g., & Walsh, S. (2001). A framework for technology management in services. *IEEE Transactions on Engineering Management, 48*(3), 333-341.

Mersha, T. (1990). Enhancing the customer contact model. *Journal of Operations Management, 9*(3), 391-405.

Michaels, G., Natraj, A., & Van Reenen, J. (2014). Has ICT polarized skill demand? Evidence from eleven countries over twenty-five years. *Review of Economics and Statistics, 96*(1), 60-77.

Mills, P. K., & Margulies, N. (1980). Toward a core typology of service organizations. *Academy of Management Review, 5*(2), 255-266.

Mills, P. K., & Turk, T. (1986). A preliminary investigation into the influence of customer-firm interface on information processing and task activities in service organizations. *Journal of management, 12*(1), 91-104.

Moeller, S. (2010). Characteristics of services–a new approach uncovers their value.

Journal of Services Marketing, 24(5), 359-368.

Murphy, P. E., & Enis, B. M. (1986). Classifying products strategically. *The Journal of Marketing*, 24-42.

O*NET. (2018). The Occupational Information Network. Available from The O*NET Resource Center, from the U.S. Department of Labor and Employment Training Administration https://www.onetcenter.org

O*NET. (2020a). O*NET Questionnaires Retrieved March 11 2020, from the U.S. Department of Labor and Employment Training Administration https://www.onetcenter.org/questionnaires.html

O*NET. (2020b). O*NET Resource Center. Retrieved March 5th, 2020, from the U.S. Department of Labor and Employment Training Administration https://www.onetcenter.org/content.html

OECD. (2019). *Measuring platform mediated workers*. Retrieved from https://www.oecd-ilibrary.org/content/paper/170a14d9-en

Pavitt, K. (1984). Sectoral patterns of technical change: Toward a taxonomy and a theory. *Research Policy, 13*, 343-373.

Peneder, M. (2003). Industry Classifications: Aim, Scope and Techniques. *Journal of Industry, Competition and Trade, 3*(1), 109-129. doi:10.1023/A:1025434721292

Perez, C. (1983). Structural change and assimilation of new technologies in the economic and social systems. *Futures, 15*(5), 357-375.

Perez, C. (2010). Technological revolutions and techno-economic paradigms. *Cambridge*

Journal of Economics, 34(1), 185-202.

Peterson, N. G., Mumford, M. D., Borman, W. C., Jeanneret, P. R., Fleishman, E. A., Levin, K. Y., . . . Pearlman, K. (2001). Understanding work using the Occupational Information Network (O* NET): Implications for practice and research. *Personnel psychology, 54*(2), 451-492.

Pfeiffer, S. (2018). The'Future of Employment'on the Shop Floor: why Production Jobs are Less Susceptible to Computerization than Assumed. *International journal for research in vocational education and training, 5*(3), 208-225.

Phillips, R. L., & Ormsby, R. (2016). Industry classification schemes: An analysis and review. *Journal of Business & Finance Librarianship, 21*(1), 1-25. doi:10.1080/08963568.2015.1110229

Polanyi, M. (1966). *The Tacit Dimension* (Foreword @ 2009 by Amartya Sen ed.): University of Chicago Press.

Prassl, J., & Risak, M. (2015). Uber, Taskrabbit, and Co.: Platforms as Employers-Rethinking the Legal Analysis of Crowdwork. *Comp. Lab. L. & Pol'y J., 37*, 619.

Price, L. L., Arnould, E. J., & Tierney, P. (1995). Going to extremes: Managing service encounters and assessing provider performance. *The Journal of Marketing*, 83-97.

Rathmell, J. M. (1966). What is meant by services? *The Journal of Marketing, 30*(4), 32-36.

Roels, G. (2014). Optimal design of coproductive services: Interaction and work allocation. *Manufacturing & Service Operations Management, 16*(4), 578-594.

Ross, M. B. (2017). Routine-biased technical change: Panel evidence of task orientation and wage effects. *Labour Economics, 48*, 198-214.

Sadun, R., Fuller, J., Hansen, S., & Neal, P. (2022). The C-Suite Skills That Matter Most More than ever, companies need leaders who are good with people. *Harvard business review, 100*(7-8), 42-50.

Sampson, S. E., & Froehle, C. M. (2006). Foundations and implications of a proposed unified services theory. *Production and Operations Management, 15*(2), 329-343.

Sanders, T., Kaplan, A., Koch, R., Schwartz, M., & Hancock, P. A. (2019). The relationship between trust and use choice in human-robot interaction. *Human factors, 61*(4), 614-626.

Schmenner, R. W. (1986). How can service businesses survive and prosper? *Sloan Management Review (1986-1998), 27*(3), 21-32.

Schmenner, R. W. (2004). Service businesses and productivity. *Decision Sciences, 35*(3), 333-347.

Schmidt, F. A. (2017). *Digital labour markets in the platform economy mapping the political challenges of crowd work and gig work*. Retrieved from Bonn, Germany: http://library.fes.de/pdf-files/wiso/13164.pdf

Shafti, F., Van Der Meer, R., & Williams, T. (2007). An empirical approach to service classification for productivity management studies. *The Service Industries Journal, 27*(6), 709-730.

Shostack, G. L. (1987). Service positioning through structural change. *The Journal of*

Marketing, 34-43.

Silvestro, R., Fitzgerald, L., Johnston, R., & Voss, C. (1992). Towards a classification of service processes. *International Journal of Service Industry Management, 3*(3), 62-75.

Skrbiš, Z., & Laughland-Booÿ, J. (2019). Technology, change, and uncertainty: maintaining career confidence in the early 21st century. *New Technology, Work and Employment, 34*(3), 191-207.

Snyder, H., Witell, L., Gustafsson, A., Fombelle, P., & Kristensson, P. (2016). Identifying categories of service innovation: A review and synthesis of the literature. *Journal of Business Research, 69*(7), 2401-2408.

Spenner, K. I. (1983). Deciphering Prometheus: Temporal change in the skill level of work. *American sociological review*, 824-837.

Spitz-Oener, A. (2006). Technical change, job tasks, and rising educational demands: Looking outside the wage structure. *Journal of labor economics, 24*(2), 235-270.

Tatasciore, M., Bowden, V. K., Visser, T. A., Michailovs, S. I., & Loft, S. (2020). The benefits and costs of low and high degree of automation. *Human factors, 62*(6), 874-896.

Theotokis, A., Vlachos, P. A., & Pramatari, K. (2008). The moderating role of customer–technology contact on attitude towards technology-based services. *European Journal of Information Systems, 17*(4), 343-351.

Thomas, D. R. (1978). Strategy is different in service businesses. *Harvard business review,* *56*(4), 158-165.

U.S. Census Bureau. (2022). North American Industry Classification System (NAICS). Retrieved June 7, 2023, from the Office of Management and Budget (OMB), https://www.census.gov/naics/

UN. (2008). *International Standard Industrial Classification of All Economic Activities Revision 4*. Retrieved from https://unstats.un.org/unsd/publication/seriesm/seriesm_4rev4e.pdf

van der Valk, W., & Axelsson, B. (2015). Towards a managerially useful approach to classifying services. *Journal of purchasing and supply management, 21*(2), 113-124.

Van Fossen, J. A., Chang, C.-H., Ford, J. K., Mack, E. A., & R. Cotten, S. (2022). Identifying Alternative Occupations for Truck Drivers Displaced Due to Autonomous Vehicles by Leveraging the O*NET Database. *American Behavioral Scientist, 0*(0). doi:10.1177/00027642221127239

Vargo, S. L., & Lusch, R. F. (2004). Evolving to a new dominant logic for marketing. *Journal of marketing, 68*(1), 1-17.

Vargo, S. L., & Lusch, R. F. (2008). From goods to service (s): Divergences and convergences of logics. *Industrial Marketing Management, 37*(3), 254-259.

Vermeulen, B., Kesselhut, J., Pyka, A., & Saviotti, P. P. (2018). The impact of automation on employment: Just the usual structural change? *Sustainability, 10*(5), 1661.

Webster, J., & Watson, R. T. (2002). Analyzing the past to prepare for the future: Writing a literature review. *MIS quarterly, 26*(2), xiii-xxiii.

Wemmerlöv, U. (1990). A taxonomy for service processes and its implications for system design. *International Journal of Service Industry Management, 1*(3), 20-40.

Whetten, D. A. (1989). What constitutes a theoretical contribution? *Academy of Management Review, 14*(4), 490-495.

Witell, L., Snyder, H., Gustafsson, A., Fombelle, P., & Kristensson, P. (2016). Defining service innovation: A review and synthesis. *Journal of Business Research, 69*(8), 2863-2872.

Wünderlich, N. V., Wangenheim, F. v., & Bitner, M. J. (2013). High tech and high touch: a framework for understanding user attitudes and behaviors related to smart interactive services. *Journal of Service Research, 16*(1), 3-20.

Wynstra, F., Axelsson, B., & van der Valk, W. (2006). An application-based classification to understand buyer-supplier interaction in business services. *International Journal of Service Industry Management, 17*(5), 474-496.

Yin, R. K. (2014). *Case study research: Design and methods* (5th ed.): SAGE Publications.

Zvegintzov, S. (1983). Services: towards a unified view. *International Journal of Operations & Production Management, 3*(3), 29-34.

Zysman, J. (2006). The algorithmic revolution---the fourth service transformation. *Communications of the ACM, 49*(7), 48.

Zysman, J., & Kenney, M. (2017). Intelligent Tools and Digital Platforms: Implications for Work and Employment. *Intereconomics, 52*(6), 329-334.

Zysman, J., Murray, J., Feldman, S., Nielsen, N. C., & Kushida, K. E. (2011). Services with everything: the ICT-enabled digital transformation of services. *BRIE Working Paper, 187a*. Retrieved from http://dx.doi.org/10.2139/ssrn.1863550

Appendix A: Example of the O*NET database of 2018

O*NET-SOC Code	Title	Element ID	Element Name	Scale ID	Scale Name	Data Value	N	Standard Error	Lower CI Bound	Upper CI Bound	Recommend Suppress	Not Relevant	Date	Domain Source
11-2021.00	Marketing Managers	2.B.3.h	Operation and Control	IM	Importance	1	8	0	1	1	N		07/2015	Analyst
11-2021.00	Marketing Managers	2.B.3.h	Operation and Control	LV	Level	0	8	0	0	0	N	Y	07/2015	Analyst
11-2021.00	Marketing Managers	2.B.3.j	Equipment Maintenance	IM	Importance	1	8	0	1	1	N		07/2015	Analyst
11-2021.00	Marketing Managers	2.B.3.j	Equipment Maintenance	LV	Level	0	8	0	0	0	N	Y	07/2015	Analyst
11-2021.00	Marketing Managers	2.B.3.k	Troubleshooting	IM	Importance	1	8	0	1	1	N		07/2015	Analyst
11-2021.00	Marketing Managers	2.B.3.k	Troubleshooting	LV	Level	0	8	0	0	0	N	Y	07/2015	Analyst
11-2021.00	Marketing Managers	2.B.3.l	Repairing	IM	Importance	1	8	0	1	1	N		07/2015	Analyst
11-2021.00	Marketing Managers	2.B.3.l	Repairing	LV	Level	0	8	0	0	0	N	Y	07/2015	Analyst
11-2021.00	Marketing Managers	2.B.3.m	Quality Control Analysis	IM	Importance	1.88	8	0.23	1.43	2.32	N		07/2015	Analyst
11-2021.00	Marketing Managers	2.B.3.m	Quality Control Analysis	LV	Level	1.38	8	0.32	0.74	2.01	N	N	07/2015	Analyst
11-2021.00	Marketing Managers	2.B.4.e	Judgment and Decision Making	IM	Importance	3.75	8	0.16	3.43	4.07	N		07/2015	Analyst
11-2021.00	Marketing Managers	2.B.4.e	Judgment and Decision Making	LV	Level	4	8	0	4	4	N	N	07/2015	Analyst
11-2021.00	Marketing Managers	2.B.4.g	Systems Analysis	IM	Importance	3.25	8	0.16	2.93	3.57	N		07/2015	Analyst
11-2021.00	Marketing Managers	2.B.4.g	Systems Analysis	LV	Level	3.75	8	0.16	3.43	4.07	N	N	07/2015	Analyst
11-2021.00	Marketing Managers	2.B.4.h	Systems Evaluation	IM	Importance	3.5	8	0.19	3.13	3.87	N		07/2015	Analyst
11-2021.00	Marketing Managers	2.B.4.h	Systems Evaluation	LV	Level	3.75	8	0.16	3.43	4.07	N	N	07/2015	Analyst
11-2021.00	Marketing Managers	2.B.5.a	Time Management	IM	Importance	3.5	8	0.19	3.13	3.87	N		07/2015	Analyst
11-2021.00	Marketing Managers	2.B.5.a	Time Management	LV	Level	3.75	8	0.16	3.43	4.07	N	N	07/2015	Analyst
11-2021.00	Marketing Managers	2.B.5.b	Management of Financial Resources	IM	Importance	2.88	8	0.13	2.63	3.12	N		07/2015	Analyst
11-2021.00	Marketing Managers	2.B.5.b	Management of Financial Resources	LV	Level	3.75	8	0.16	3.43	4.07	N	N	07/2015	Analyst
11-2021.00	Marketing Managers	2.B.5.c	Management of Material Resources	IM	Importance	2.62	8	0.18	2.27	2.98	N		07/2015	Analyst
11-2021.00	Marketing Managers	2.B.5.c	Management of Material Resources	LV	Level	2.75	8	0.16	2.43	3.07	N	N	07/2015	Analyst
11-2021.00	Marketing Managers	2.B.5.d	Management of Personnel Resources	IM	Importance	3.38	8	0.18	3.02	3.73	N		07/2015	Analyst
11-2021.00	Marketing Managers	2.B.5.d	Management of Personnel Resources	LV	Level	3.88	8	0.13	3.63	4.12	N	N	07/2015	Analyst
11-2022.00	Sales Managers	2.A.1.a	Reading Comprehension	IM	Importance	3.88	8	0.13	3.63	4.12	N		07/2016	Analyst
11-2022.00	Sales Managers	2.A.1.a	Reading Comprehension	LV	Level	4	8	0	4	4	N	N	07/2016	Analyst
11-2022.00	Sales Managers	2.A.1.b	Active Listening	IM	Importance	4	8	0	4	4	N		07/2016	Analyst
11-2022.00	Sales Managers	2.A.1.b	Active Listening	LV	Level	4	8	0	4	4	N	N	07/2016	Analyst
11-2022.00	Sales Managers	2.A.1.c	Writing	IM	Importance	3.62	8	0.18	3.27	3.98	N		07/2016	Analyst
11-2022.00	Sales Managers	2.A.1.c	Writing	LV	Level	4	8	0	4	4	N	N	07/2016	Analyst
11-2022.00	Sales Managers	2.A.1.d	Speaking	IM	Importance	4	8	0	4	4	N		07/2016	Analyst
11-2022.00	Sales Managers	2.A.1.d	Speaking	LV	Level	4.12	8	0.13	3.88	4.37	N	N	07/2016	Analyst
11-2022.00	Sales Managers	2.A.1.e	Mathematics	IM	Importance	3	8	0	3	3	N		07/2016	Analyst
11-2022.00	Sales Managers	2.A.1.e	Mathematics	LV	Level	3.25	8	0.16	2.93	3.57	N	N	07/2016	Analyst
11-2022.00	Sales Managers	2.A.1.f	Science	IM	Importance	1.62	8	0.18	1.27	1.98	N		07/2016	Analyst
11-2022.00	Sales Managers	2.A.1.f	Science	LV	Level	0.62	8	0.18	0.27	0.98	N	N	07/2016	Analyst
11-2022.00	Sales Managers	2.A.2.a	Critical Thinking	IM	Importance	3.88	8	0.13	3.63	4.12	N		07/2016	Analyst
11-2022.00	Sales Managers	2.A.2.a	Critical Thinking	LV	Level	4	8	0	4	4	N	N	07/2016	Analyst
11-2022.00	Sales Managers	2.A.2.b	Active Learning	IM	Importance	3.75	8	0.16	3.43	4.07	N		07/2016	Analyst
11-2022.00	Sales Managers	2.A.2.b	Active Learning	LV	Level	3.88	8	0.13	3.63	4.12	N	N	07/2016	Analyst
11-2022.00	Sales Managers	2.A.2.c	Learning Strategies	IM	Importance	3.25	8	0.16	2.93	3.57	N		07/2016	Analyst
11-2022.00	Sales Managers	2.A.2.c	Learning Strategies	LV	Level	3.75	8	0.16	3.43	4.07	N	N	07/2016	Analyst
11-2022.00	Sales Managers	2.A.2.d	Monitoring	IM	Importance	3.75	8	0.16	3.43	4.07	N		07/2016	Analyst
11-2022.00	Sales Managers	2.A.2.d	Monitoring	LV	Level	4.75	8	0.16	4.43	5.07	N	N	07/2016	Analyst
11-2022.00	Sales Managers	2.B.1.a	Social Perceptiveness	IM	Importance	3.88	8	0.13	3.63	4.12	N		07/2016	Analyst
11-2022.00	Sales Managers	2.B.1.a	Social Perceptiveness	LV	Level	4.12	8	0.13	3.88	4.37	N	N	07/2016	Analyst
11-2022.00	Sales Managers	2.B.1.b	Coordination	IM	Importance	3.88	8	0.13	3.63	4.12	N		07/2016	Analyst
11-2022.00	Sales Managers	2.B.1.b	Coordination	LV	Level	4.12	8	0.13	3.88	4.37	N	N	07/2016	Analyst
11-2022.00	Sales Managers	2.B.1.c	Persuasion	IM	Importance	4.12	8	0.13	3.88	4.37	N		07/2016	Analyst
11-2022.00	Sales Managers	2.B.1.c	Persuasion	LV	Level	4.38	8	0.18	4.02	4.73	N	N	07/2016	Analyst
11-2022.00	Sales Managers	2.B.1.d	Negotiation	IM	Importance	3.88	8	0.13	3.63	4.12	N		07/2016	Analyst
11-2022.00	Sales Managers	2.B.1.d	Negotiation	LV	Level	3.88	8	0.13	3.63	4.12	N	N	07/2016	Analyst
11-2022.00	Sales Managers	2.B.1.e	Instructing	IM	Importance	3.62	8	0.18	3.27	3.98	N		07/2016	Analyst
11-2022.00	Sales Managers	2.B.1.e	Instructing	LV	Level	3.62	8	0.18	3.27	3.98	N	N	07/2016	Analyst
11-2022.00	Sales Managers	2.B.1.f	Service Orientation	IM	Importance	3.88	8	0.13	3.63	4.12	N		07/2016	Analyst
11-2022.00	Sales Managers	2.B.1.f	Service Orientation	LV	Level	3.88	8	0.13	3.63	4.12	N	N	07/2016	Analyst
11-2022.00	Sales Managers	2.B.2.i	Complex Problem Solving	IM	Importance	3.75	8	0.16	3.43	4.07	N		07/2016	Analyst
11-2022.00	Sales Managers	2.B.2.i	Complex Problem Solving	LV	Level	3.88	8	0.23	3.43	4.32	N	N	07/2016	Analyst
11-2022.00	Sales Managers	2.B.3.a	Operations Analysis	IM	Importance	2.62	8	0.18	2.27	2.98	N		07/2016	Analyst

Appendix B: Example of the O*NET database of 2003

O*NET-SOC Code	Element ID	Element Name	Scale ID	Data Value	Date	Source
11-2021.00	2.B.3.m	Quality Control Analysis	IM	1.75	3/2002	Legacy Analyst
11-2021.00	2.B.3.m	Quality Control Analysis	LV	1.5	3/2002	Legacy Analyst
11-2021.00	2.B.4.e	Judgment and Decision Making	IM	4.33	3/2002	Legacy Analyst
11-2021.00	2.B.4.e	Judgment and Decision Making	LV	5.5	3/2002	Legacy Analyst
11-2021.00	2.B.4.g	Systems Analysis	IM	4.11	3/2002	Legacy Analyst
11-2021.00	2.B.4.g	Systems Analysis	LV	5.83	3/2002	Legacy Analyst
11-2021.00	2.B.4.h	Systems Evaluation	IM	3.5	3/2002	Legacy Analyst
11-2021.00	2.B.4.h	Systems Evaluation	LV	4.67	3/2002	Legacy Analyst
11-2021.00	2.B.5.a	Time Management	IM	3.16	3/2002	Legacy Analyst
11-2021.00	2.B.5.a	Time Management	LV	4.66	3/2002	Legacy Analyst
11-2021.00	2.B.5.b	Management of Financial Resou	IM	3	3/2002	Legacy Analyst
11-2021.00	2.B.5.b	Management of Financial Resou	LV	4.66	3/2002	Legacy Analyst
11-2021.00	2.B.5.c	Management of Material Resour	IM	2.5	3/2002	Legacy Analyst
11-2021.00	2.B.5.c	Management of Material Resour	LV	3.83	3/2002	Legacy Analyst
11-2021.00	2.B.5.d	Management of Personnel Reso	IM	3.33	3/2002	Legacy Analyst
11-2021.00	2.B.5.d	Management of Personnel Reso	LV	3.66	3/2002	Legacy Analyst
11-2022.00	2.A.1.a	Reading Comprehension	IM	3.9	3/2003	Incumbent
11-2022.00	2.A.1.a	Reading Comprehension	LV	4.28	3/2003	Incumbent
11-2022.00	2.A.1.b	Active Listening	IM	4.47	3/2003	Incumbent
11-2022.00	2.A.1.b	Active Listening	LV	4.49	3/2003	Incumbent
11-2022.00	2.A.1.c	Writing	IM	3.51	3/2003	Incumbent
11-2022.00	2.A.1.c	Writing	LV	4.34	3/2003	Incumbent
11-2022.00	2.A.1.d	Speaking	IM	4.21	3/2003	Incumbent
11-2022.00	2.A.1.d	Speaking	LV	4.16	3/2003	Incumbent
11-2022.00	2.A.1.e	Mathematics	IM	4.17	3/2003	Incumbent
11-2022.00	2.A.1.e	Mathematics	LV	3.63	3/2003	Incumbent
11-2022.00	2.A.1.f	Science	IM	2.2	3/2003	Incumbent
11-2022.00	2.A.1.f	Science	LV	1.71	3/2003	Incumbent
11-2022.00	2.A.2.a	Critical Thinking	IM	3.66	3/2003	Incumbent
11-2022.00	2.A.2.a	Critical Thinking	LV	4.32	3/2003	Incumbent
11-2022.00	2.A.2.b	Active Learning	IM	3.81	3/2003	Incumbent
11-2022.00	2.A.2.b	Active Learning	LV	4.28	3/2003	Incumbent
11-2022.00	2.A.2.c	Learning Strategies	IM	3.47	3/2003	Incumbent
11-2022.00	2.A.2.c	Learning Strategies	LV	4.24	3/2003	Incumbent
11-2022.00	2.A.2.d	Monitoring	IM	3.9	3/2003	Incumbent
11-2022.00	2.A.2.d	Monitoring	LV	5.07	3/2003	Incumbent
11-2022.00	2.B.1.a	Social Perceptiveness	IM	3.91	3/2003	Incumbent
11-2022.00	2.B.1.a	Social Perceptiveness	LV	4.39	3/2003	Incumbent

Appendix C: Job Zone reference of 2018 from the O*NET

(Source: “db_23_0_aug: Job Zone Reference.xlsx” and "Job Zone Reference - O*NET 27.0 Data Dictionary" of the National Center for O*NET Development; license: CC BY 4.0)

Job Zone Number	Job Zone Name and Description	Experience	Education	Job Training	Examples
1	Job Zone One - Little or No Preparation Needed	Little or no previous work-related skill, knowledge, or experience is needed for these occupations. For example, a person can become a waiter or waitress even if he/she has never worked before.	Some of these occupations may require a high school diploma or GED certificate.	Employees in these occupations need anywhere from a few days to a few months of training. Usually, an experienced worker could show you how to do the job.	These occupations involve following instructions and helping others. Examples include counter and rental clerks, dishwashers, sewing machine operators, landscaping and groundskeeping workers, logging equipment operators, and baristas.

2	Job Zone Two - Some Preparation Needed	Some previous work-related skill, knowledge, or experience is usually needed. For example, a teller would benefit from experience working directly with the public.	These occupations usually require a high school diploma.	Employees in these occupations need anywhere from a few months to one year of working with experienced employees. A recognized apprenticeship program may be associated with these occupations.	These occupations often involve using your knowledge and skills to help others. Examples include orderlies, forest firefighters, customer service representatives, security guards, upholsterers, and tellers.
3	Job Zone Three - Medium Preparation Needed	Previous work-related skill, knowledge, or experience is required for these occupations. For example, an electrician must have completed three or four years of apprenticeship or several years of vocational	Most occupations in this zone require training in vocational schools, related on-the-job experience, or an associate degree.	Employees in these occupations usually need one or two years of training involving both on-the-job experience and informal training with	These occupations usually involve using communication and organizational skills to coordinate, supervise, manage, or train others to accomplish

		training, and often must have passed a licensing exam, in order to perform the job.		experienced workers. A recognized apprenticeship program may be associated with these occupations.	goals. Examples include hydroelectric production managers, travel guides, electricians, agricultural technicians, barbers, court reporters, and medical assistants.
4	Job Zone Four - Considerable Preparation Needed	A considerable amount of work-related skill, knowledge, or experience is needed for these occupations. For example, an accountant must complete four years of college and work for several years in accounting to be considered qualified.	Most of these occupations require a four-year bachelor's degree, but some do not.	Employees in these occupations usually need several years of work-related experience, on-the-job training, and/or vocational training.	Many of these occupations involve coordinating, supervising, managing, or training others. Examples include accountants, sales managers, database administrators, graphic designers, chemists, art directors, and cost estimators.

5	Job Zone Five - Extensive Preparation Needed	Extensive skill, knowledge, and experience are needed for these occupations. Many require more than five years of experience. For example, surgeons must complete four years of college and an additional five to seven years of specialized medical training to be able to do their job.	Most of these occupations require graduate school. For example, they may require a master's degree, and some require a Ph.D., M.D., or J.D. (law degree).	Employees may need some on-the-job training, but most of these occupations assume that the person will already have the required skills, knowledge, work-related experience, and/or training.	These occupations often involve coordinating, training, supervising, or managing the activities of others to accomplish goals. Very advanced communication and organizational skills are required. Examples include librarians, lawyers, astronomers, biologists, clergy, surgeons, and veterinarians.

Appendix D: Skill categories according to the O*NET

(Source: "The O*NET® Content Model" of the National Center for O*NET Development; license: CC BY 4.0; accessed March 5th, 2020 https://www.onetcenter.org/content.html)

Category	Subcategory	Element	Definition
Basic skills	Content	Active Listening	Giving full attention to what other people are saying, taking time to understand the points being made, asking questions as appropriate, and not interrupting at inappropriate times
		Mathematics	Using mathematics to solve problems
		Reading Comprehension	Understanding written sentences and paragraphs in work related documents
		Science	Using scientific rules and methods to solve problems
		Speaking	Talking to others to convey information effectively
		Writing	Communicating effectively in writing as appropriate for the needs of the audience
	Process	Active Learning	Understanding the implications of new information for both current and future problem-solving and decision-making
		Critical Thinking	Using logic and reasoning to identify the strengths and weaknesses of alternative solutions, conclusions or approaches to problems
		Learning Strategies	Selecting and using training/instructional methods and procedures appropriate for the situation when learning or teaching new things

		Monitoring	Monitoring/Assessing performance of yourself, other individuals, or organizations to make improvements or take corrective action
Cross-functional skills	Social skills	Coordination	Adjusting actions in relation to others' actions
		Instructing	Teaching others how to do something
		Negotiation	Bringing others together and trying to reconcile differences
		Persuasion	Persuading others to change their minds or behavior
		Service Orientation	Actively looking for ways to help people
		Social Perceptiveness	Being aware of others' reactions and understanding why they react as they do
	Complex Problem-Solving Skills	Complex Problem Solving	Identifying complex problems and reviewing related information to develop and evaluate options and implement solutions
	Technical Skills	Equipment Maintenance	Performing routine maintenance on equipment and determining when and what kind of maintenance is needed
		Equipment Selection	Determining the kind of tools and equipment needed to do a job
		Installation	Installing equipment, machines, wiring, or programs to meet specification
		Operations Analysis	Analyzing needs and product requirements to create a design
		Operation and Control	Controlling operations of equipment or systems

	Operation Monitoring	Watching gauges, dials, or other indicators to make sure a machine is working properly
	Programming	Writing computer programs for various purposes
	Quality Control Analysis	Conducting tests and inspections of products, services, or processes to evaluate quality or performance
	Repairing	Repairing machines or systems using the needed tools
	Technology Design	Generating or adapting equipment and technology to serve user needs
	Troubleshooting	Determining causes of operating errors and deciding what to do about it
System Skills	Judgment and Decision Making	Considering the relative costs and benefits of potential actions to choose the most appropriate one
	Systems Analysis	Determining how a system should work and how changes in conditions, operations, and the environment will affect outcomes
	Systems Evaluation	Identifying measures or indicators of system performance and the actions needed to improve or correct performance, relative to the goals of the system
Resource Management Skills	Management of Financial Resources	Determining how money will be spent to get the work done, and accounting for these expenditures
	Management of Material	Obtaining and seeing to the appropriate use of equipment, facilities, and

	Resources	materials needed to do certain work
	Management of Personnel Resources	Motivating, developing, and directing people as they work, identifying the best people for the job
	Time Management	Managing one's own time and the time of others

Abstract (Korean)

기술 변화는 사회경제제도 안에서 법, 규제, 산업, 제도 및 근로자 등 여러 요인이 관계를 맺으며 연속적이고 역동적으로 발생한다. 따라서 기존 연구 방식을 재검토하고 기술 발전에 대한 현재의 논점을 지속해 확장하는 것이 중요하다. 본 논문에서는 기술과 서비스, 기술과 일의 관계를 중심으로 기술변화가 일과 서비스에 미치는 영향을 정성적으로 분석한다.

첫째, 서비스를 정의하고 분류하는 체계로서 서비스 분류를 연구한다. 정보통신 기술은 전반적으로 서비스에 영향을 미치며, 플랫폼 서비스와 같은 다양한 서비스가 기술의 발전과 함께 등장하고 있다. 따라서 첫 번째 연구 목적은 기존 서비스 분류 유형을 파악하고 새로운 속성을 제안하여 플랫폼 서비스의 특성을 파악할 수 있는 서비스 분류 체계를 제안하는 것이다.

체계적인 문헌 검토를 통해 기존 분류 간의 유사성을 파악하고, 어떤 속성이 존재하며 어떻게 특정 속성 유형으로 분류할 수 있는지 분석한다. 분석된 속성을 적용하여 기존의 서비스 분류 속성이 새로운 서비스를 설명할 수 있는지 논의하고, 플랫폼 서비스의 사례를 분석하여 기존 속성 유형의 단점을 확인한다. 기존 분류는 새로운 비즈니스 또는 기술적으로 변형된 서비스 프로세스에 대한 변화를 다루지 않기 때문에 플랫폼 서비스를 설명하기에는 불충분하다. 이러한 분석 결과를 바탕으로 기존 서비스 분류에 대한 포괄적인 속성 유형과 플랫폼 서비스에 대한 추가 속성 유형을 제안한다. 정의된 특성과 유

형은 다양한 서비스를 설명하고 기술 발전 때문인 변화를 설명하는 데 도움이 될 수 있다.

기술이 산업의 형태를 바꿀 수 있는 만큼, 이러한 변화는 그 산업에서 일하는 사람들에게도 영향을 미친다. 따라서 관련 요소를 고려하여 기술 변화에 대한 설명이 향상되어야 한다. 기술이 작업을 수행할 수 있고, 노동자는 이러한 작업에서 대체될 수 있다. 또한, 인간의 노동이 기계보다 비교우위에 있는 새로운 업무가 창출될 가능성이 있으며, 이는 신규 채용 및 고용 증가로 이어질 수 있다. 그러나 기술 변화에 따른 직무수행에 필요한 기술의 변화는 직무와 비교하면 기존 연구에서 크게 주목받지 못했다. 따라서 두 번째 연구 목적은 직무수행 기술과 직무의 변화를 관찰하여 직업 내 변화를 이해하는 것이다. 이러한 변화를 이해하기 위해 계산원의 사례를 연구하였다. 계산원의 직무와 직무수행 기술은 더 상호작용적이고 인지적이며 사회적인 요소에 초점을 맞추도록 변화했다. 사회적 기술은 이러한 작업을 컴퓨터나 기계가 쉽게 할 수 없기에 더 주목받고 있다. 계산원 사례 연구를 통해 하나의 직업에 집중함으로써 그 안에서의 변화를 더 깊이 이해할 수 있었다.

계산원 사례 연구에 이어 직무 수행에 필요한 직무수행 기술을 더 자세히 분석한다. 직업 내, 직업 간 직무수행 기술 변화의 흐름을 분석하여 기존 기술과 시간이 지남에 따라 중요성이 높아진 기술에 관하여 연구한다. 세 번째 연구 목적은 여러 직업에 대한 직무수행 기술의 변화를 분석하는 것이다. 37개의 직업이 분석되었으며, 대부분의 직무수행 기술이 시간이 지남에 따라 변화했음을 연구에서 확인했다. 또한, 정규 교육 수준과 같은 직무수행 기술 관

련 요인에 따라 직무수행 기술의 변화를 분석했다. 모든 직업의 사회적 기술은 상당한 변화를 보였으며, 협상과 설득은 시간이 지남에 따라 그 중요성이 더 커졌다. 이 연구는 직무수행 기술을 암묵적 지식과 명시적 지식 유형으로 분류하여 직무수행 기술 변화를 살펴보고 기존 직무수행기술 정의 방법의 한계를 해결하고자 했다. 결과 분석을 통해 본 연구는 직무수행 기술 변화를 포착하고 설명할 수 있는 모델을 제시한다.

결과적으로, 본 논문은 기술 발전에 따른 변화를 다른 관점에서 연구하는 것의 중요성에서 시작하여 질적 연구 방법을 통해 기술변화, 일, 노동자의 직무수행 기술 간의 역학 관계를 이해하고자 했다. 이를 위해 일과 서비스에서의 기술변화를 연구하여 이들이 기술 변화에 어떻게 반응하고, 그 변화를 어떻게 설명할 수 있는지 파악했다. 또한, 이번 연구는 서술적 데이터를 활용한 정성적 연구 방법이 유기적이고 지속적인 변화의 세부 사항을 파악하고 전체적인 흐름을 이해할 수 있음을 보여줌으로써 정성 분석이 의미 있는 연구 접근법이 될 수 있음을 밝혔다.

주요어 : 기술 변화, 직무수행 기술, 직무, 일, 노동자, 서비스 분류
학 번 : 2014-31108