THE ROLE OF AI TO ENHANCE RETIREMENT SAVINGS:

THE GENDER GAP CHALLENGE

BY

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ABSTRACT

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Keywords: Gender gap, pension, retirement savings, artificial intelligence, AI readiness, labour force gap, women retirement, gender disparity. GGP, AI.

Abstract:

AI is the biggest disruptor in the financial sector, where there are many AI solutions at work, and the role of AI over it is well documented. However, the deployment of AI in the pension segment is still at an exploratory stage, and its influence on the gender gap in pensions is still unclear. This research explores the relationship between AI readiness and the gender gap in pensions (GGP), which may also be statistically significant. In addition, this research examined the relationship between AI and some of the main factors that could influence the GGP to provide meaningful data on how AI can affect them. This research involves a review of the literature regarding GGP, AI readiness, and potential AI solutions that the pension sector can adopt to improve women's retirement savings. The analysis includes descriptive data, Spearman's correlation test, and multiple linear regression. Subsequently, the discussion focused on the role of AI on the GGP, the labour force gender gap, the income gender gap, and education. One limitation of the study was that the data on the GGP, only a few countries have standardized data. Nevertheless, this research also found a statistical equation that can predict more than 50% of the variation of the GGP value using only four predictors.

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Preface

My experience working in the Pensions sector allowed me to learn about various issues people face regarding pensions and identify crucial areas that need improvement in this sector. There is a lack of initiatives to explore the potential of AI and use technology from a gender perspective. Furthermore, the gender gap in pension income is a significant problem exacerbated by other factors. This dissertation aims to provide meaningful insights into how AI can help improve women's retirement savings. I believe the effective use of artificial intelligence can improve the pension sector and change how it faces gender challenges.

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For me, as a reminder that the journey has been worth it, each step brought me here and will take me further. Este trabajo es para mis amados padres, quienes me apoyaron en esta aventura. Arantxa y Anais, mis cómplices en la vida y mi motivación diaria. Juntas nos hemos hecho fuertes, son mi razón para ser una mejor persona cada día.

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Anabel Martinez Colin
Bradford, UK. September 2022.

Acronyms

AI: Artificial intelligence
AML: Anti-money laundering
EU: European Union
EUC: European Commission
FinTech: Financial Technology
GGG: Global Gender Gap
GGP: Gender Gap in Pension
IOPS: International Organisation of Pension Supervisors
ITU: International Telecommunication Union
IRCAI: International Research Centre in Artificial Intelligence
KYC: Know Your Customer
ML: Machine Learning
NLP: Natural Language Processing
STEM: Science, Technology, Engineering and Mathematics
UNDP: United Nations Development Programme
WEF: World Economic Forum

Chapter 1: Introduction

1.1. Introduction

Gender Gap in Pensions (GGP) is the term used to describe the difference between women's and men's income received from public and private pensions at the end of their working life (OECD, 2021c). However, the gender gap results from what women face throughout their labour history (OECD, 2021a). Women face different challenges in accumulating contributory periods for retirement throughout their working life affecting their pension (Clements et al., 2014). This effect is real regardless of the pension system design in different countries. However, this effect has a remarkable impact in defined contribution systems where the benefit received depends entirely on the resources accumulated during working life. The benefits are affected by salary level throughout working life; higher salary and more contributions result in better benefits at retirement (OECD, 2021a).

The lack of equity that affects women's work history varies from a deficit of opportunities, unequal salary levels, deficiency of quality jobs, lower access to strategic positions, and others (Foster, 2018). In most pension schemes, pension depends on work history. Thus, when men and women retire, there is a significant difference in their pensions (OECD, 2021a). In countries like Mexico, Austria, Luxembourg, France, and the UK, the GGP is greater than 30% (OECD, 2021a). As a result, women in those countries tend to receive less than 30% of the pension that men can access.

Against this backdrop, technology has been making significant advances that allow key decision makers to identify the gender gap to provide insights on alternatives to address the challenge. AI and its applications in the financial industry are helping to design new products and services, help reach new market sectors, predict people's needs and behaviours, and discover anomalies, and trends (Akerkar, 2019). AI is changing the financial industry, the economy, and the labour market. Financial and non-financial institutions are embracing AI solutions (Mhlanga, 2020). Additionally, governments are implementing AI to provide efficient and quality public services, extend social security, and develop environments to maximize the benefits (Oxford Insights, 2019). AI and ML can help explore new scenarios to develop policies to improve women's retirement savings, increase contributions and contribution periods, enhance women's finances and education, obtain better pension plan, among others.

1.2. Problem Statement

The GGP is a problem that continues to grow and affects women. Gender gaps in pensions by nation fluctuate from 3% to 47% (OECD, 2021a). The GGP reveals the cumulative impact of all differences women face in the labour market (Clements et al., 2014). Women have lower employment rates than men, are more likely to work part-time jobs, receive lower wages (Lis & Bonthuis, 2019). Additionally, elder women in many countries are more likely than men to fall into poverty. The average poverty rate for women is 16.2% and for men is 11.6%. Women's pension income, their life expectancy, and depending on family income represent a risk for women (OECD, 2021a). Previous analyses suggest that by 2050 women could only receive 80% of the pension received by men (Smith-Carrier et al., 2021). It is necessary to guarantee that women get access to a retirement pension to cover their needs and prevent them from falling into poverty (OECD, 2021a). At the present time, with the available solutions, some countries temporarily mitigate the risks (Clements, 2014). AI can produce new insights for policymakers and improve market labour conditions for women, reducing the motherhood penalty in contributions, among others. AI-based solutions can change how to address the GGP.

However, to use AI to decrease GGP, the country should have an environment ready to adopt and use its potential. A national AI strategy is necessary for countries with strong adoption of AI and a solid research and innovation foundation (Oxford insights, 2019. Countries must have the right tools and an environment to obtain the benefits of AI-driven technological transformation.

1.3. Research Purpose

The research aims to provide insights regarding the role of AI and the retirement savings gender gap by measuring the statistical relationship between the AI readiness variables and the GGP. A second objective of the research is to explore the possible relationship between GGP, AI readiness variables, and other factors that could influence the GGP. The research has an exploratory approach, and its importance lies in being the first study that test the statistical relationship between AI readiness indicators, the gender gap in pension, and factors that could impact the GGP. In addition, the academic literature review contributes to identifying possible AI solutions that can help to enhance the retirement saving of women and reduce the GGP. The research looks to build a foundation for future research to improve women's retirement savings and implement AI solutions in the pension sector.

1.4. Research Questions

The research questions are founded on findings from the literature review.

1. Is there a statistical relationship between the indicators of AI readiness and the Gender gap in pension? What are the potential AI-based solutions that could help reduce the GGP?
2. Does relationship exist between the GGP and other variables from the dataset?
3. Is there a statistical relationship between the indicators of AI readiness and other gender gap indicators such as the labour force gap or the income of women?

1.5. Relevance and Importance of the Research

Pensions from the gender perspective are a little-studied topic, and AI is underdeveloped in this sector; its effect is still uncertain (IOPS, 2018). However, this is exploratory research to test statistically the impact of AI on the GGP. AI is an enabler for many subjects and a disruptor in other financial areas (Mhlanga, 2020). Even when AI is helping to test and analyse new scenarios to decrease poverty and increase financial inclusion, its applications in pensions still are few. AI and ML are revealing the value of data, empowering the interpretations to get significant insights, and enhancing data-driven decision-making (Turner, 2019). It is possible to take the knowledge and benefits that AI has brought to other research areas and adapt this know-how to face the gender gap in pensions. This project aims to encourage the implementation of AI in pensions to tackle the gender gap in retirement savings and be the first to provide statistical data about the effect of AI in Pensions from a gender perspective.

1.6. Limitations & Assumptions

The main assumptions are that the AI readiness level could influence the gender gap in pensions, alongside other factors that affect the GGP. One limitation of the research is that it was not feasible to find literature with conclusive statistical data or previous studies regarding the application of AI in Pensions from a gender perspective. Another limitation is the use of secondary data because each variable was collected originally for different purposes, and data is not updated in the same period; these conditions can affect the effectiveness of the analysis and results. The research could not include all countries and did not focus on any particular country as GGP information was limited. The limitations on data availability prevent the research from studying the global spectrum of the gender gap in retirement savings.

1.7. Study Outline

The research is organized into five chapters to assess the role of AI in improving women's retirement savings. Chapter two presents a literature review of factors related to GGP and an overview of AI in the financial and pension sectors. The literature review provides the theoretical framework for this research and outlines the main themes for readers. Chapter three presents the research methodology, including a description of the techniques, elements, and data involved in the study. Subsequently, chapter four presents the descriptive data, correlational analysis, and multiple regression tests. Finally, chapter five describes the main findings and develops the discussion, summarizing the conclusions and suggestions based on the information and results from the previous chapters. Thus, the structure includes:

- Chapter One: Introduction and problem statement
- Chapter Two: Literature Review
- Chapter Three: Methodology Research
- Chapter Four: Data Analysis
- Chapter Five: Findings, Conclusions and Suggestions

Chapter 2: Literature Review

2.1. Introduction

This chapter introduces the academic background of the study, and the purpose is to review and analyse the literature about the gender gap, pensions, and AI. First, this paper introduces the gender gap in retirement savings, illustrating the potential factors that affect women's retirement savings. Second, it presents an overview of Artificial Intelligence and the importance of the readiness for the development and adoption of AI. Finishing with a review of the AI-based solutions in the financial sector and pensions and describing how it can address women's issues to improve their retirement savings.

2.2. Gender Gap in retirement savings

2.2.1. Global Gender Gap

The GGP has recently taken on vital importance for some countries. A first step before talking about GGP is to provide an overview of the Global Gender Gap. The Global Gender Gap Index measures gender inequality across the world, ranking nations according to the proximity to gender equality. The index analyses areas of inequality between men and women and involves wages, levels of economic participation, and access to employment, among others (WEF, 2022).

The GGG report 2022 evaluated 146 countries in four contexts health, political, economic, and education. The report indicates 94.4% gender gap in education is almost closed, however, it estimates that reaching gender parity could take more than 130 years. Also, the gender gap in the economic dimension persists, and the results estimate it could be closed in 151 years (WEF, 2022). The WEF indicated the gender gap in the economic dimension increased between 2013 and 2017. According to WEF (2022) many factors still affect women's labour trajectories. Women usually earn less than men and accumulate lower wealth, while also their pension is related to the contributions during working life, which depend on job wages (EUC, 2015). Consequently, the GGP is not deliberate is the effect of what has happened throughout women's labour history (Criado-Perez, 2019).

2.2.2. Factors of the Gender gap in retirement savings

Labour market conditions, low payment, lack of financial literacy, and unequal financial access impede women's ingress to banking, investments, and retirement saving options (WEF, 2022). The gender gap becomes exacerbated in pension due to its accumulative compound effect in the long term. Prabhakar (2022) mentions three principal factors: labour market conditions, demographic differences, and the design of pension systems. Following this line, the WEF (2022) studied wealth equity in 39 countries. The result shows some factors to affect women accumulating wealth in working life are gender pay gap, unequal career progression, lack of financial literacy, and life events like maternity. These factors decrease their proportion in workforce participation, and employment time directly impacts retirement contributions and wealth accumulation (WEF, 2022).

Currently, social rules and socioeconomic and legal context influence women's choice in education and career along working life (WEF, 2022). All of them have some impact on the capacity of women to prepare for their retirement. The labour force gap remains substantial in developing countries such as India, Argentina, Brazil, Mexico, and others. Emergency nations also have elevated rates of teenage maternity and high numbers of young women who are not working, studying, or training (ILO & OECD, 2019). Besides, the COVID-19 pandemic has altered the dynamics at home and work. These limits reduced business activity and resulted in high job losses and shorter working hours. In 2021, employment loss reached around 144 million jobs (WEF, 2021). The GGG analysis showed that in the labour market from 2020, gender equality decreased rapidly. As a result, gender equality in the labour force in 2022 was 62.9%, the smaller level registered since 2006. Also, unemployment levels have grown in the last two years and remain elevated for women (WEF, 2022).

The rise in women's unemployment rates could correspond partially to the negative effect of Covid-19, and another direct cause is that unpaid care work (WEF, 2022). The impact of motherhood penalty is a significant factor in low wealth accumulation for women (Prabhakar, 2022; WEF, 2022). Kleven at el. (2019) made an analysis that revealed women experience a constant decrease in their income after the birth of the first child. Women generally cannot recover from the decrease in income. Overall, their study found that maternity penalties stem from the impact of three factors: job supply, hours of labour supply (part-time jobs), and wage rate. Furthermore, the maternity penalty also brings additional challenges, such as difficulties re-entering the workforce after inactivity in childcare and discrimination against elder women trying to ingress the labour market (ILO & OECD, 2019). Thus, the living conditions of women, the maternity penalty, and interruptions in the work career drive women to postpone retirement and work longer to compensate for the wealth disparity and achieve a full pension (Jędrzychowska et al., 2020).

Furthermore, due to the COVID-19 pandemic, the demand for childcare increased as schools closed, and more than two million mothers around the world left their jobs in 2020 (WEF, 2022). The labour force participation of parents decreased during the pandemic, but in November 2020, in the US, fathers successfully regained labour participation, while the labour force rate of mothers was even worse, with 2.8 percentage points less than the previous year (WEF, 2022). However, before the pandemic, 75% of unpaid work was carried out by women, spending between three and six hours per day (Criado-Perez, 2019). Therefore, childcare, and the reduction of women's labour participation add challenges for women to generate wealth (WEF, 2022).

For Lis & Bonthuis (2019), the labour market is a crucial driver of the GPP; their research shows that women in full-time employment usually work 4.9 years fewer than males (in the EU) and work an estimated 3.3 years more in a part-time job. The working life interval is a critical factor in the GGP because women usually have a shorter career life in the EU because of their home care duties (Lis & Bonthuis, 2019). In contrast, men have longer career and work more frequently in full-time jobs. The gap in duration in full-time employment reached 15 years in Switzerland and the Netherlands. In several nations, the women workforce is concentrated in part-time jobs (Holzmann et al., 2020). The WB (2014) indicated that part-time work provides women flexibility but involves lower earnings, fewer perks and protection, and no career progression. The WB (2014) study shows that women in part-time with specific profiles were considerably more likely to get less payment than men with same profile. For Holzmann et al. (2020), part-time work negatively impacts on women’s wealth accumulation because this kind of job affecting career development and incomes.

In addition, women are more likely to get a low-pay positions without opportunities for scale-up (WB, 2014). The gender pay gap is remarkable; it was around 14% across EU countries (Holzmann et al., 2020). Also, women have less access to employers that can provide a private pension plan, while males are more likely to find a job with a private retirement plan (Dietz et al., 2003). The report of ILO & OECD (2019) reveals that women are more often in low-paid full-time jobs (less than two-thirds of the average salary). Across the G20 countries, a third and a half of women in full-time employment are in low-paid jobs. Recently, 2022 revealed a modest decrease in the gender pay gap partially because women received +2% more and men earned -1.8% less than in 2021. Thus, the speed for closing the gap is still long the equity remains low in most countries (WEF, 2022). The analysis made by Mavrikiou and Angelovska (2020) revealed the gender pay gap impact tends not to be higher for the GGP in some EU countries. Even with a smaller gender pay gap, some EU countries have a higher GGP mainly due to their labour market conditions, such as many women in part-time jobs and substantial differences by gender in the length of job-careers. A different EU nations group presented a higher gender wage gap; but fewer gender differences in working life duration and lower women proportion in part-time jobs, resulting in a lower GGP. Thus, the labour-market conditions significantly influence the gender pension gap (Mavrikiou & Angelovska, 2020).

In general, shorter careers are equal to a large GGP, sometimes gap increase with the duration of the career break. However, the GGP sometimes can decrease when people have steady jobs during working life, which is more common in the public sector (EUC, 2015). The length of a career is a critical variable that affects the GGP because the breaks career affects the asset of women, who can expect shorter careers with 4.2 years less than men. In almost half of the EU countries, the gender gap in career time is more than three years (Lis & Bonthuis, 2019). In Italy, this gap is close to 7 years, and there is lower participation of women in the labour force (Holzmann et al., 2020). Enhancing women's participation in the labour market involves companioning them through work-life changes, such as a first job, maternity, career progress, and retirement. To decrease the effect, some countries like Australia and UK introduced measures to support women's return after a career break. Initiatives include re-skill, vocational training, job counselling, childcare services, child benefits, sponsorships (ILO & OECD, 2019).

Women face a gender pay gap but also deal with sorting mechanisms in the labour market, such as educational options and occupational and sectoral opportunities. Nolan et al. (2019) found that employment and education remarkably influence the GGP. Also, women are likely to choose more jobs in social areas, education, and health than in STEM areas. In the words of UNESCO et al. (2022), AI can impact women working lives; because women have less access to technology, lack digital skills, and have less participation in STEM affecting the labour positions and wages. To close the gender gap in occupational and sectoral opportunities, women should have equal opportunities to get education and training (Lis & Bonthuis, 2019). In fields generally dominated by males, the stakeholders should open more inclusive and equal job environments (UNESCO et al., 2022). Holzmann et al. (2020) analysed the employment gap and noticed it in Poland increased when both genders had less than tertiary-level education. Also, their study indicates Sweden practically does not have an employment gap between genders with tertiary education but still has a GGP of over 28% (WEF, 2022; OECD, 2021c). Holzmann et al. (2020) also found a tendency when people with higher education regularly incorporate into the workforce later but have more steady careers.

Besides, their study considers that the labour market offers better opportunities for people without career breaks and fewer permanent positions for persons with career breaks. In addition, poverty in older people also seems significantly associated with the educational level. The poverty rates for people with secondary-level education or less are around four times that for people that completed the first or second phases in tertiary-level (Clements et al., 2014). Also, Nolan et al. (2019) observed that pensioners with secondary education have a 17% higher pension than people with primary education, and graduates show a pension 57% higher. Thus, improving education for women can help decrease the gender gap in employment and reflect differences in the GGP.

In addition, financial education can facilitate women to reach acceptable pension conditions. Younger women need to comprehend how to save money and accumulate enough wealth for pensions (Clements et al., 2014). Overall, pension illiteracy is related to the misunderstanding of pensions and the lack of knowledge of pensioners' rights (Holzmann et al., 2020). One study finds that financial education has a higher positive impact on saving and investment rates than only providing information about savings and pensions (Clements et al., 2014). According to Speelman et al. (2013), gender influences financial decisions, and women tend to avoid risk and prefer more conservative investments. The analysis also indicates that younger women prefer lower-risk options, and older women tend to make investments with better returns within a moderate framework. Financial education combined with AI tools can encourage women to invest from a young age and improve women's savings and investment decisions.

Conventionally, women in a relationship depend on the male pension, which usually has a better income pension than women (Holzmann et al., 2020). But personal financial choices can be more critical sooner. The OECD’s (2021a) report shows several changes in the pensions system. For instance, Italy, Ireland, and others increased early-retirement options. New Zealand increased contribution options, Lithuania and Poland designed auto-enrolment schemes, and Estonia modified mandatory contributions as voluntary (OECD, 2021a). Holzmann et al. (2020) indicated a crucial influence of financial education on financial decisions and pension contributions. Several countries offered financial education and noticed a positive impact on retirement preparation. Financial education provides the foundation for developing savings plans and avoid debt on the retirement edge. (Holzmann et al., 2020). However, the GGP reflects the problems that women face throughout their lives. The literature reflects the complicated interactions between the GGP and other variables. It is a priority to enhance women's financial autonomy, decreasing income differences and gender disparity in pensions.

2.3. General overview of Artificial Intelligence

AI is transforming tasks and jobs, with algorithms and neural networks shaping various industrial sectors from recommendations and predictions to robotics and more applications (Skilton & Hovsepian, 2018). The OECD definition of AI involves a machine-based system that can make decisions for real or virtual situations, make forecasts and predictions, and suggestions (OECD/RBC, 2019). Recently, many solutions for the financial sector use different AI tools, such as speech and audio processing, neural network, speech recognition, text mining, geographic information, and satellite imaging, among others (WB, 2018).

Furthermore, the algorithms and AI make feasible advanced technology and specialized functionalities. For instance, expert systems are commonly used in the insurance and financial sector as credit underwriting, investment advisories, banking management, and more (Davenport, 2018). NLP is collecting data from social media to estimate credit ratings, analyse stock markets, and decide if an individual is likely to be valuable in a job position (Rau et al., 2021). The insurance companies have amounts of data in vehicle pictures, AI applications can offer insurance policy based on a photograph (WEF, 2018).

2.3.1. AI readiness

AI is the most disruptive innovation affecting the entire financial sector, including retirement savings systems. Compared with other areas of the financial industry, the improvement in the pension area is still at an emerging and exploratory stage (IOPS, 2018). However, following the EUC (2020) to move AI forward, a country requires an ecosystem with trust policies, a human-centric approach, dynamic data, AI skilled workforce, and investment. Europe has developed an ecosystem with a solid infrastructure (EUC, 2020). The AI ecosystem of each country needs to improve data, increase public datasets, and enhance technical infrastructure (Tang, 2022). Skilled force work is required to support this ecosystem, and many adopters are looking to quickly increase capacity by bringing in new skilled labour (Hupfer, 2020). For instance, women's participation in STEM online courses grew from 31% to 38% in 2020 (NESCO et al., 2022). Several studies suggest that AI could affect existing jobs, and occupations held by people with low education are more likely to be affected than those held by people with higher education. The statistical models suggest that a potential increase in the demand for skilled staff can compensate for the initial job losses (Frontier economics, 2018).

In general, the high technologic solutions require infrastructure to support digital operations, such as data availability, telecommunications networks, data servers, etc. The ecosystem provides an environment that allows AI to exploit digital resources and opportunities (Park et al., 2021). Also, incorporation of AI drives a change in the nation's organization. Digital readiness usually leads to an innovative, positive, and reliable approach to adopting new digital solutions in any field, including the pensions sector.

Some countries with supportive infrastructure and capabilities are leading and going ahead in AI adoption. Oxford Insights produced the Government AI Readiness Index to measure the ability of each nation to adopt and use AI (Oxford Insights, 2019). As might be anticipated, the highest ranked countries in this index are nations with strong economies, developed AI strategies, and innovative industries (Oxford Insights, 2019). According to the Oxford 2021 report, Europe is over the general average due to governments working to obtain the benefits of AI tools, combined with trusted economies and a digitally skilled population. However, Eastern European nations are stressed by their political environment, struggling with the current economic imbalance. Political instability makes it difficult for some countries to build the reliable infrastructure and framework required to develop and deploy AI (Oxford Insights, 2021).

Surprisingly, some Latin American countries appear over the general average in AI Readiness Index, such as Brazil, Chile, Mexico, and Colombia. However, for developing countries is a challenge to build the technical capacity to deploy AI solutions. The key challenges to increase the use of AI include strategies, capability, and adequate resources (Montoya & Rivas, 2019). The data and infrastructure required to support AI development are growing slowly (Oxford Insights, 2021). The biggest challenges are access to reliable data without potential bias and representativeness because developing countries have ethnic groups and a low-income population that are not in any database (Oxford Insights, 2020). Even with the progress of some countries, the index shows inequality in AI readiness due to a lack of data, infrastructure, and skilled workforce (Oxford Insights, 2021).

2.3.2. AI Solutions in financial sector

Due to digital transformation in finance activities, the sector has become one of the crucial information sources. The influence of AI on the financial sector has prompted the public sector to pursue the use and understanding of AI (OECD, 2021b). Also, AI is creating valuable insights, early warning systems, and predictive analysis on different topics for sustainable development and programmatic response (ITU, 2018).

AI has had a disruptive effect on the financial sector, mainly in six areas. Obtaining information to predict customer behaviour, forecast their solvency, etc. Cybersecurity: Early detection and prevention of fraud in identity verification processes. KYC/AML: simplifying regulatory and regulatory compliance. Process optimization: the creation of accounts, review of documentation, etc. Chatbots: Smartly engage with customers, reduce customer support burdens, etc. Facilitating access to services: Use data analysis to assess the solvency of clients without traditional documentation or with informal income (IFC, 2021). For instance, Leo is a personal virtual banker from Nigeria and is one good example of an AI-based system that provides a faster response with high customer satisfaction and accessibility. Customers can chat with Leo at any time using messenger, telegram, or WhatsApp (Kshetri, 2021). The financial sector recognized the benefits of using technology and AI to reduce human error and help generate new products and one-stop services. AI-based solutions are bigger financial industry disruptors (Park et al., 2021).

The following lines explore some AI solutions in the financial sector and pensions. AI chatbots help provide individual assistance, helping clients with easy tasks such as opening an account, paying bills, and transferring money, among others (Golić, 2019). AI technology could assist women in opening a private pension plan or changing administrator pension funds, among other formalities and procedures. Currently, some initiatives are operating in the pension sector, such as Dream Forward chatbot (Confusion index) incorporates decision trees and sentiment analysis (Invesco, 2019). In smart loans, AI helps access new data sources to understand and explain complex patterns in customer data. The credit provider uses this information set a new credit scoring system based on AI, including wealth data from smartphones and alternative data points to provide access to credit from financial institutions (Golić, 2019). AI algorithms could help to reduce information asymmetry and allocate women's pension accounts. Smart Sales AI systems and chatbots can be virtual salespeople and answer customer inquiries (Golić, 2019). A virtual salesperson could guide women in the registration process for pension funds, setting recurrent savings, and other procedures.

In smart trading, AI can make quick trading decisions using ML algorithms capable of making predictions and finding anomalies in the market to make better decisions about buying, selling, and holding stocks (Golić, 2019). It could offer the best deals in managing women's pension funds. For example, Mercer's ML algorithm establishes the probability that a participant will accept personalized offers. Also, AI guides the customer to make better decisions and solve problems with pension arrangements (Consultancy UK, 2020). Robo-advisor, work with algorithms to build an individual financial portfolio according to the goals algorithm can make predictions about expenses and investments to act as a personal financial advisor (Golić, 2019). Another example is a Robo-advisor (e.g., Clarity Money, MoneyLion) that analyses customer patterns, recommends funds, and registers financial decisions to make advice options (IFC, 2021; WEF, 2018). This technology could be adapted with knowledge of pension funds and offer a similar service.

AI solutions to track retirement savings include virtual assistants like Alexa, which track pension contributions in the UK, the customer, can ask how much the retirement savings are worth today and how much their contributions are (PensionsAge, 2018). The pension dashboard provides a one-stop shop for people to view their retirement savings status across public and private pension plans, bringing transparency. AI in marketing communications can use behavioural insights to boost interest in retirement savings or increase contributions and savings (OECD, 2018). Review of paperwork, AI is speeding up the processing of paperwork to decrease times from hours to seconds (WEF, 2018). With this adoption, the claims and requests for benefits are transforming into a one-stop service. Also, an insurance company developed self-executing parametric agreements to compensate clients and eliminate the claims process (WEF, 2018). In pension, this solution could adopt it to self-issue of pension benefits. In management, AI allows detailed insight for insurers, who can visualize risks and generate crucial information for their clients, such as the probability of natural disasters or health risks (WEF, 2018). AI could generate detailed insight to make precise recommendations to women regarding their retirement savings according to their specific context, such as regular information about their funds and behaviour consumer. Integrated services platforms are building complete financial ecosystems (WEF, 2018). Pension-fund managers could be included in this ecosystem to find and reach women within the system. For example, in Kenya, to address the coverage problem in retirement savings, Mbao creates a pension plan for informal sector workers (IOPS, 2018).

In the same direction, FinTech enterprises are adopting AI to extend financial inclusion (IFC, 2021). One example of AI addressing information asymmetry is Konfio, Mexican FinTech, which provides loans in about 24 hours using an AI-based score credit (Kshetri, 2021). Another example is MyBucks, from Africa, which offers insurance and microloans. The AI solution scrapes data from the cell phone of a potential borrower and generates a profile to assess creditworthiness (IFC, 2021). Another is ALGEBRA from Malaysia, using AI targets people with specific religious beliefs. The financial Robo-Adviser offers advice with sharia-compliant and non-compliant investment options. ALGEBRA sets goals for its clients, then the ML recommends stocks, prepares a risk-weighted portfolio, and manages the portfolio (Kshetri, 2021). Increasing financial inclusion is essential to improve the living standards of women.

Consequently, AI is helping to address digital financial inclusion issues such as documentation requirements, costs, and literacy (Mhlanga, 2020).

2.3.3. AI addressing Sustainable Development Goals

Beyond commercial purposes, multiple applications of AI are being explored to achieve development objectives and social good (WB, 2018). AI is helping aim sustainable development goals, such as monitoring income, predicting poverty, tracking policies and practices, detecting and correcting gender bias, and optimizing recruitment for employers and job seekers, among others (WB, 2018). The IRCAI (2021), supported by UNESCO tracked AI. Their last report considers 100 AI applications, the result shows that 12,7% could help tackle poverty, 29.7% improve quality education, 29.1% help reach general gender equality, and 31.8 % contribute to generating decent work and economic growth. For UNESCO et al. (2022), AI can improve market conditions for women, preventing and tracking gender bias in job announcements and measuring its impact. For example, Textio is an AI-based solution that helps reduce inequality and poverty, decreasing the gender gap in labour offered by detecting biased language patterns. Job advertisements use almost double the quantity of masculine-tone than feminine-tone phrases in positions that hire a man (UNESCO et al., 2022). Also, CompIQ, Gapsquare, PIHR, and PAR platforms are initiatives looking to increase fair pay for women (Tschopp, 2021).

In terms of education and equality, the Argentine government implemented an AI solution to predict teenage pregnancy and school dropout. The government then issued an outline to develop a program to strengthen young women's commitment to education (OECD/CAF, 2022). In addition, Malta implemented an AI to help students achieve better educational outcomes and classify early school leavers (Misuraca & van Noordt, 2020). An example of solving childcare problems is the AI system from Poland that allocates children to individual nurseries. Other examples are the Harambee youth employment accelerator that used AI to improve the conversion rate of candidates and the job search. The Red Cross uses AI to forecast the financing of disaster funds in Togo (Ohlenburg, 2020). The Polish government uses AI to profile people who can access unemployment benefits. In Dublin, the government uses AI for sentiment analysis through citizen tweets to learn about their important concerns (Misuraca & van Noordt, 2020).

2.4. Conclusions

AI can help address the disparity women face in the financial and labour market from different perspectives. Current literature indicates a wide range of elements affect women's ability to accumulate savings for retirement, mainly because it depends on professional career and working conditions. However, the literature reveals how AI is addressing gender challenges and improving conditions for vulnerable groups. AI can analyse different scenarios with ML to find hiding patterns, factors, and trends that could impact the GGP. Provide personalized assistance to women, using precise language (e.g., Textio, ALGEBRA) to enhance their interest, setting up personalized financial advice, and offering friendly one-stop services. Also, AI can improve financial literacy by providing new tools for financial education and lowering risk aversion. Facilitating the understanding of pensions (e.g., gamification) and summarizing important information (e.g., arXiv, ROUGE). Provide new elements and tools for a better understanding of the challenges of women in pensions (sentimental analysis such as SemEval and Confusion index). Furthermore, the literature review and the use cases demonstrate the capability of AI to change the labour market conditions for women. AI can help provide insights to define new policies and benefits, address problems like childcare, maternity penalties, gender pay gap, prevention dropping education, and target programs to reincorporate women after career breaks. There is a world of unknown options, several countries are developing AI solutions focused on financial applications, and others are looking for a solution to address poverty and economic disparity.

Chapter 3: Methodology

This segment addresses the methodology utilized in this research, including the research philosophy and research design. After that, it presented the variables employed in this research and the methods implemented. Lastly, it discusses the data analysis techniques and data collection.

The Saunders research onion model considers that any research project begins by selecting the research philosophy to simplify the gradual development of the layers. Selecting the proper approach and methodology facilitates the identification of procedures and methods required for the data analysis (Saunders et al., 2016). In the word of Kazdin (2003), methodology refers to the principles, procedures, and practices to lead the research, and disseminating the results.

3.1. Research philosophy

The research philosophy is the base of the project. It can be described as a set of beliefs indicating the ideology that the researcher will use in studying a subject. Positivism is one of the principal research philosophies, and it works based on an observable reality to produce credible data and facilitate replication (Saunders et al., 2016). In the opinion of Saunders et al. (2016), ontological assumptions address the nature of the phenomenon, its origin, interpretation in a specific context, and what point of view the researcher chose to interpret the reality and answer the research question.

According to the nature of the research and its objectives, the appropriate philosophy for this study is positivism, which establishes an external, impartial, and independent point of view of social actors. This research is an exploratory study and pursues positivism to provide knowledge based on observable phenomena and insights within other sectors.

3.2. Research Design

The most important goal of the research is to provide insights regarding the role of AI and the gender gap in pensions using ML techniques, looking for statistical significance between the AI readiness by country and the GGP. The study uses the data from OECD, which evaluated the GGP in OECD members. In congruence with the literature review, this research studied few factors such as the labour force gender gap, income gender gap, and other factors previously mentioned to analyse their possible correlation with the gender gap in pension.

To measure the role of AI is essential to consider that AI transformation requires the proper tools and operating environment. In line with McKinsey (2018), some macro factors impact AI development, such as national infrastructure, labour-market structure, a strong economy, and the environment for transition to AI. The Government AI Readiness Index assesses the conditions of each country to implement AI (Oxford Insights, 2021). It evaluates three main pillars in each country: Government, the technology sector, data & infrastructure. These pillars measure the AI national strategy, capabilities, infrastructure, and data availability, among other crucial factors that can influence the development of AI. Therefore, due to the importance of these factors, this research considers these three main pillars to represent the development level of each country.

3.3. Data analysis techniques

Data analysis has various approaches and incorporates different techniques (Marczyk et al., 2005). This research includes cross-tabulation, descriptive analysis, Spearman test, and multiple linear regression analysis. To answer the research questions is necessary to study the relationship between the GGP and the variables in the dataset. However, finding a relationship between two variables does not indicate that the first variable can produce the second one (Akerkar, 2018). The relationship could be positive or negative, and the correlation coefficient shows the strength of the relationship, a value closer to zero shows a weaker relationship (Embarak, 2018). A positive relationship indicates that the variables change in the same direction; a negative relationship means that as one data increase, other data decrease (Marczyk et al., 2005).

3.3.1. Data analysis plan

First, the research includes a descriptive analysis to provide an overview of the crucial data using descriptive statistics and graphic representation to find meaningful insights. Second, the study involves a correlation test due to data including rank values and scores of international indicators, the most widespread technique to research the possible correlation between ordinal data is the Spearman correlation coefficient (Saunders et al., 2016). Also, the Spearman test can determine the strength and direction even in a non-monotonic and non-linear relationship with the highest confidence intervals even with a small dataset (Bishara & Hittner, 2017). Thus, due to the data characteristics and the exploratory nature of the research, the analysis considers Spearman correlation. The correlation analysis performance involves too scatterplots and heatmap. Scatterplot helps identify the possible relationship between two variables, identify patterns or clusters and detect extreme values, and helps to interpret the correlation coefficients (Knaflic, 2015). Heatmap is a graphical representation commonly used in ML to represent in a colourful matrix the value and magnitude of the correlation coefficient for every two variables compared, and the colours allow an easy and intuitive interpretation (Sharda et al., 2019; Knaflic, 2015). Furthermore, the importance of heatmap comes when the dataset has many features, it allows for a quick screening of which data should be considered for deeper analysis (Baesens, 2014). This part of the study is divided into two parts one focused on the GGP, and the other focused on AI readiness and its relationship with the other variables.

Third, this research includes multiple regression analysis to discover what factors are associated with the GGP due to multiple regression helping to predict a dependent variable using one or more independent variables (Saunders et al., 2016). The method involved in the multiple linear regression to reach the best b coefficients is Ordinary Least Squares (OLS) which is well-studied and frequently performed in python (Masís, 2021). Then, the GGP is set as the dependent variable (DV) in different models to find the optimal model. The process consists of observed different combinations of predictors (IVs) and their main values until find which model have better perform and meet main assumptions (Masís, 2021). Select the optimal model include interpretation of main values as the coefficient of determination (R^2) that represents the percentage of the variation in a DV that can be explained statistically by the IVs (Saunders et al., 2016). Also, interpret the model significance, to be sure the effect is not likely to have occurred by coincidence (Saunders et al., 2016).

3.4. Dataset and data collection

The research uses quantitative secondary data to achieve unbiased analysis and ensure the reliability of the data collected. Data collection was done online considering the latest information available for each subject (at the moment of collection) from formal reports including sources such as UNDP, WEF, Oxford Insights, Eurostat, and OECD. Data time frame considers information published in 2020, 2021, and 2022. The data include the most recent evaluation of the GGP was carried out and published by the OECD (2021c), is the latest official report dedicated to assessing the gap between the retirement income received by women and the income received by men in OECD member countries.

AI readiness involves assessing strategy, human talent, processes, technology, data, platforms, and infrastructure (Deloitte, 2020). For this research, AI readiness is the capacity of each country to deploy and use the potential of AI in ways that sum value to the country's development (Oxford insights, 2017; Holmström, 2021). Thus, the research includes the variables from the AI Readiness Index to represent the current capability and AI development level by country. In addition, the literature indicates that the main factors influencing the GGP are the labour market conditions as salary, workforce gap, and education (Lis & Bonthuis, 2019; Prabhakar, 2022). Then, the dataset considers variables that can provide information regarding gender disparity in the labour market like as wage, education, and labour force. These variables were widely studied by some authors like Nolan et al. (2019), Lis & Bonthuis (2019), and Holzmann et al. (2020). They reported a relationship between them and the GGP. For instance, they found that higher education is related to better pension income, better labour conditions, and better wage that improve pension contributions. Besides, these authors studied and found that labour force participation and the gender pay gap impact pension contributions.

3.4.1. Countries included

The OECD assessed the GPP in 34 OECD member countries in the 2021 report. To ensure the global picture of the GGP is more accurate, the analysis aims to include as many countries as possible. The Dataset included eight additional countries with formal and standard GGP information from Eurostat. Dataset considers only countries where the last GGP calculated for 2020 or 2021, the latest available at the collection date. The economies considered in the research are:

Albania, Australia, Austria, Belgium, Bulgaria, Canada, Chile, Colombia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Japan, Latvia, Lithuania, Luxembourg, Malta, Mexico, Montenegro, Netherlands, North Macedonia, Norway, Poland, Portugal, Romania, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom, and United States of America.

Chapter 4: Data Analysis

The research looks for statistical associations between the GGP and the dataset variables. This research aims to provide meaningful insights, answer the research questions, and show the potential of AI and ML. First, the chapter reveals the results of the descriptive analysis to depict an overview of the principal data. After, to measure the role of AI and the influences of other factors in the GGP, the research involves the Spearman test, followed by a multiple linear regression analysis to find which factors could influence the GGP. Lastly, it shows the AI readiness interaction with other factors such as income, labour force, and education.

4.1. Descriptive Analysis

The dataset contains 42 countries, 34 economies are from Europe, and the rest have a small representation. The distribution is detailed in Figure 1. Due to a lack of GGP data, some regions are not represented in the study. To increase the representativeness in future research it is necessary to extend the measurement of GGP in nations outside the EU.

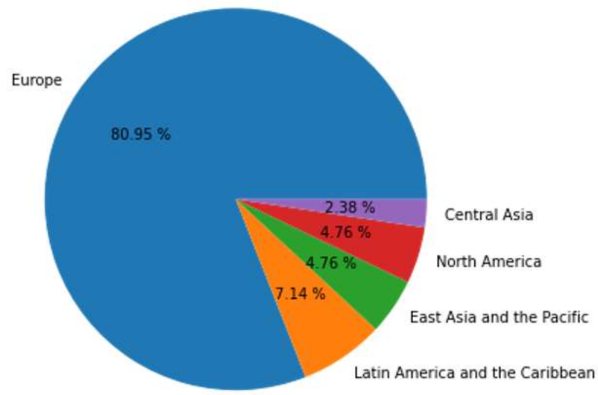

Figure 1- Distribution by region
(Source: Author)

The descriptive statistics in Table 1 show that the countries considered in the research reported a minimum score of 42.90 in AI readiness, with higher value for data and infrastructure pillar, where the average is 77.20. That means the dataset includes several countries with better AI readiness than the global statistics, where the minimum score is 17.93, and the mean value in the infrastructure pillar is 58.43 (WEF, 2021). It is essential to keep this in mind due to global disparities regarding AI, and the effect of AI could differ from the information generated in this research.

Table 1 - Descriptive Statistics
(Source: Author)

Variable	Mean	Std Deviation	Min	Max
GGP	24.81	10.64	3.30	47.40
AI Overall Score	65.94	10.47	42.90	88.16
Data Infrastructure	77.20	9.46	55.99	92.71
Government	70.21	13.12	40.71	88.46
Tech Sector	50.42	12.46	28.54	83.31
Income Gap	15.82	7.54	4.17	37.40
Income Score	0.67	0.08	0.43	0.83
Income Male	48.81	22.71	15.24	131.05
Income Women	32.99	16.66	10.98	93.65
Labour Force Score	0.79	0.09	0.46	0.91
Labour Force Gap	13.70	6.49	6.36	37.56
Mean Years of Schooling Men	11.93	1.37	8.30	14.43
Mean Years of Schooling Women	11.72	1.58	7.28	13.88
Secondary Gap	3.95	4.26	0.06	18.84
Secondary Male	111.83	19.01	80.83	165.74
Secondary Women	107.87	16.66	74.49	146.90
Tertiary Gap[a]	18.26	11.12	0	49.91
Tertiary Male[a]	81.87	26.74	0	150.05
Tertiary Women[a]	63.61	23.83	0	147.08
Wage Score[b]	0.65	0.13	0	0.85

a: Japan did not show information for this item

b: Norway did not show information for this item

The mean of GGP is 24.8, the minimum value reported was 3.3, and the max was 47.4. Figure 2 shows the distribution by the number of countries and their GGP value. The top 10 are the ten countries with the smaller GGP values, which are from 3.3 to 15.5, the smaller value better parity. In addition, 20 countries are above the average, of which the Netherlands, Luxembourg, the UK, Japan, and others reported a GGP above 40.

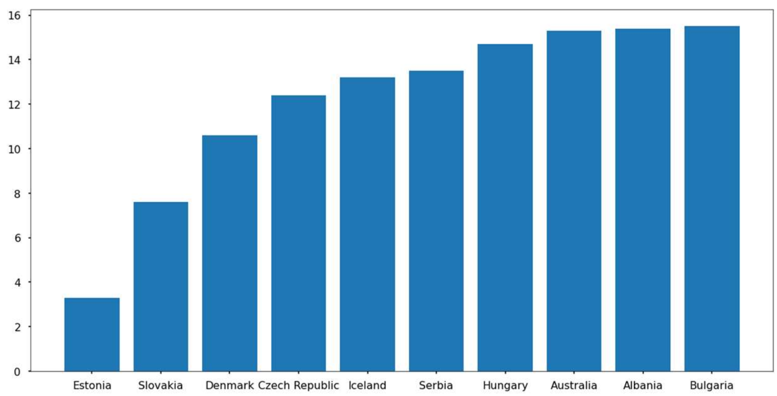

Figure 2 - Top10 countries with smaller GGP
(Source: Author)

Regarding the AI readiness, the minimum value reported in the overall score is for Albania, and the gap with the first place is 45.6. Top10 in the overall score include US, Canada, Denmark, Germany, Sweden, United Kingdom, and others. The minimum score reported among the three pillars is 28.54 for the tech sector, and the maximum score is 92.71 for the infrastructure pillar. Figure 3 illustrates the differences between top10 economies and countries with an overall score under 55. The pillar with fewer differences is infrastructure, and most countries are struggling to develop the tech sector pillar.

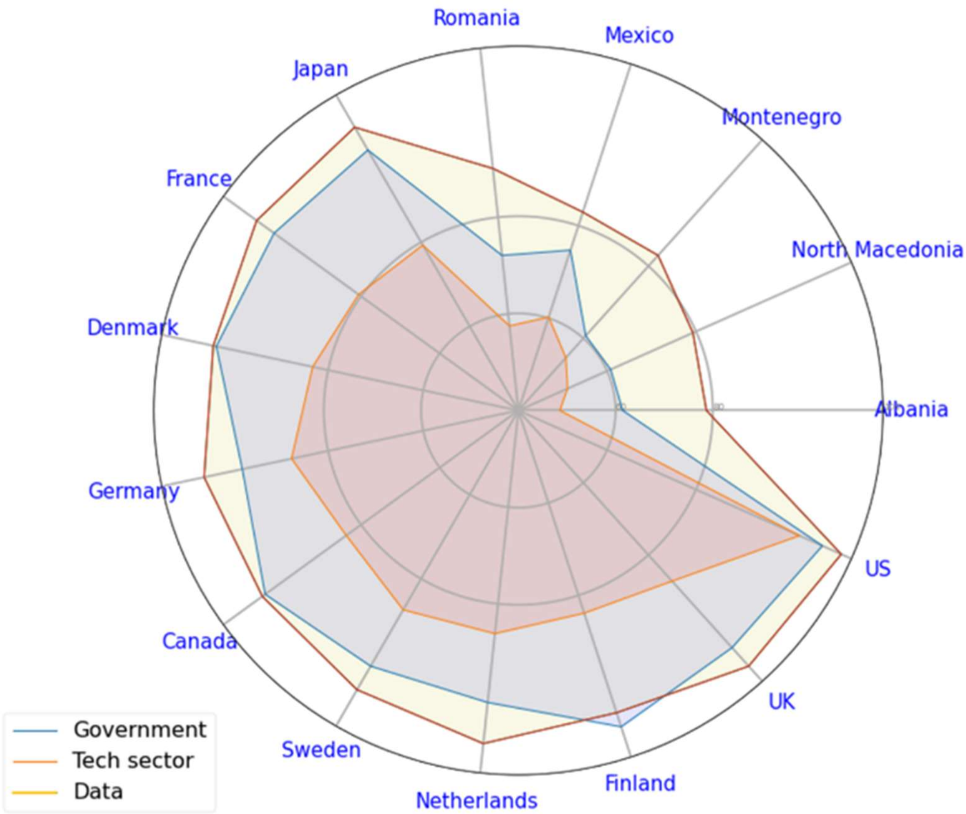

Figure 3 - Differences in AI readiness pillars
(Source: Author)

The average gap in estimated income was 15.82K, and 18 countries in the dataset are over this number. The top10 of countries where the gap is less than 10k include Albania, Bulgaria, Portugal, Lithuania, Sweden, and others. Figure 4 shows the list of ten countries with a higher gap in the dataset. Luxembourg and Ireland are the only two countries that reported an estimated income for men over 100k. The maximum value reported for women was 93.65K.

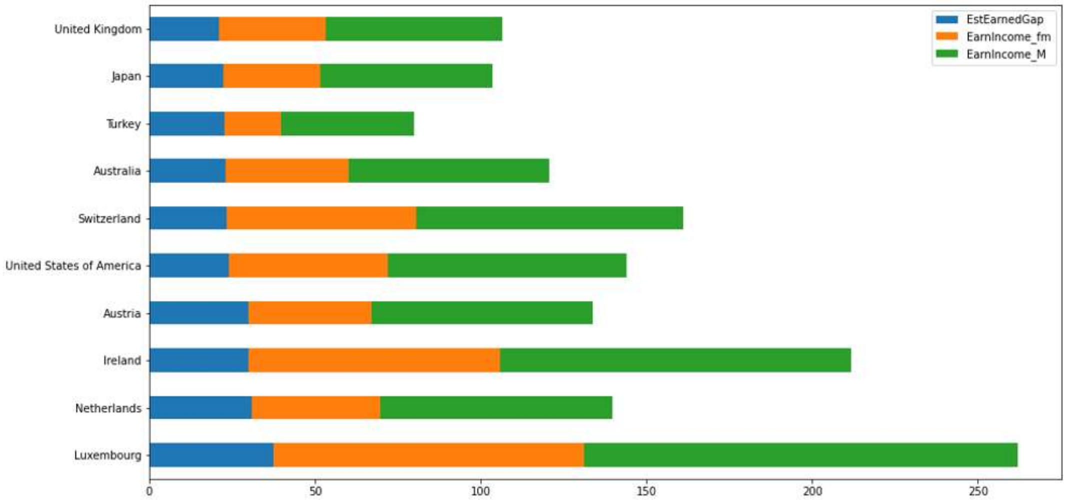

Figure 4 - Economies with larger income gap
(Source: Author)

The values of Table 1 show similar numbers for the GGP and the income gap. Also, graphic representation shows that GGP tends to follow very close the income gap variation as is depicted in Figure 5.

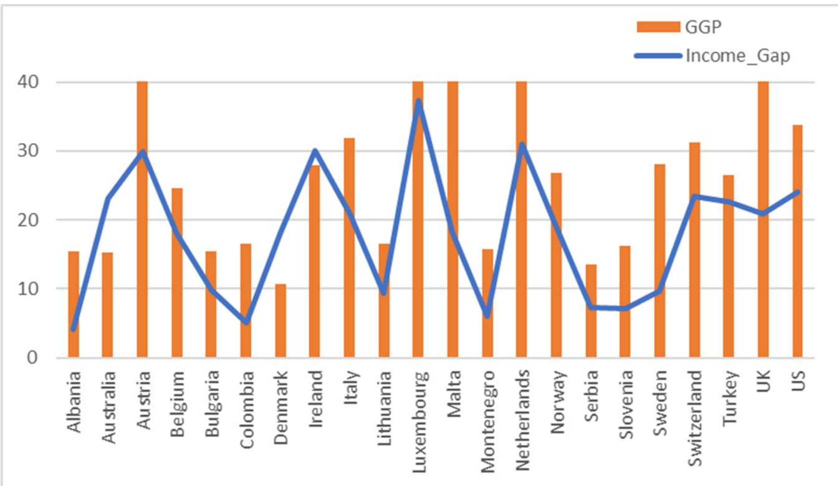

Figure 5 - GGP and Income Gap
(Source: Author)

Besides, the graphic representation of income for women and men shows that tech sector values tend to have similar variation that income for both genders, but mainly is close to variation of men income as is depicted in Figure 6.

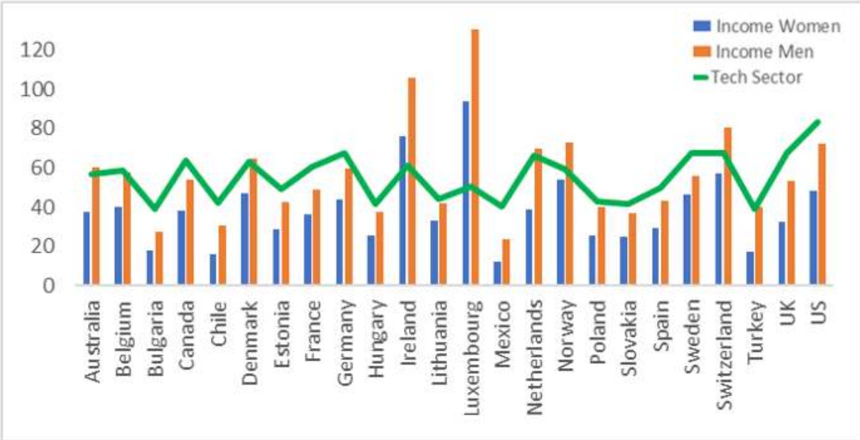

Figure 6 - Tech sector vs Income
(Source: Author)

In addition, the average labour force gap was 6.36, and the maximum value reported was 37.56. The mean was 13.7, and 26 economies were under the average. However, as is depicted in Figure 7, several countries with a low labour force gap have a higher GGP as Luxembourg, France, the Netherlands, and others. Some cases have higher levels of labour force gap and GGP, such as Mexico, Turkey, Japan, and others, where women face the biggest challenges in the labour force market and the retirement stage.

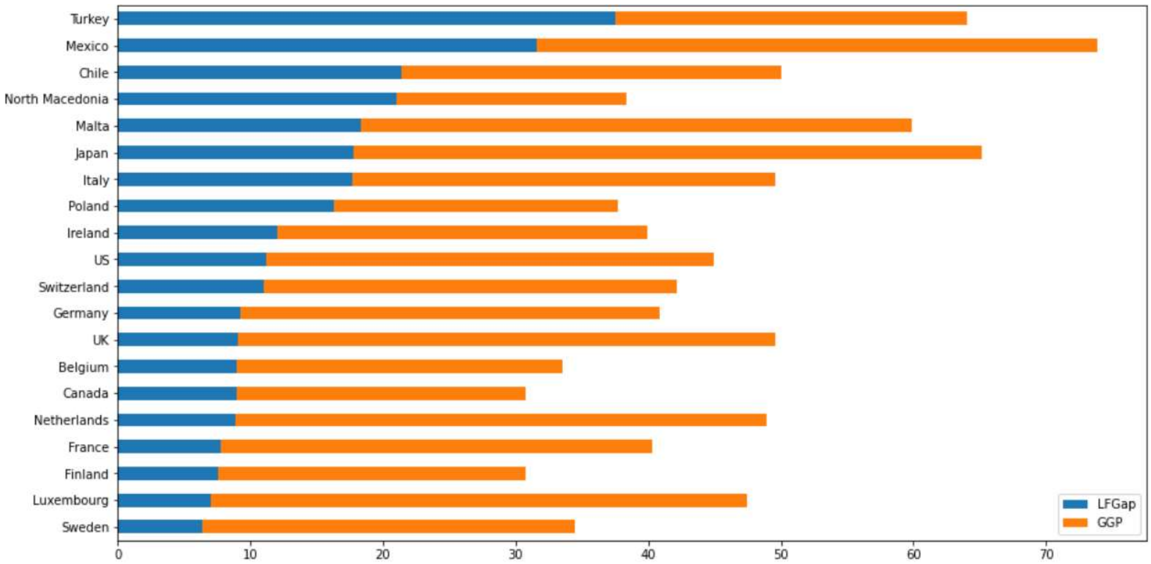

Figure 7 - Labour Force Gap vs GGP
(Source: Author)

Concerning women's education, many economies are closing the gap in enrolment at the secondary level. However, several countries show a significant difference between the number of women enrolled at the secondary and women enrolled at the tertiary education as detailed in Figure 8. All the nations in the graphic show a gap over 45% between women enrolled by level education.

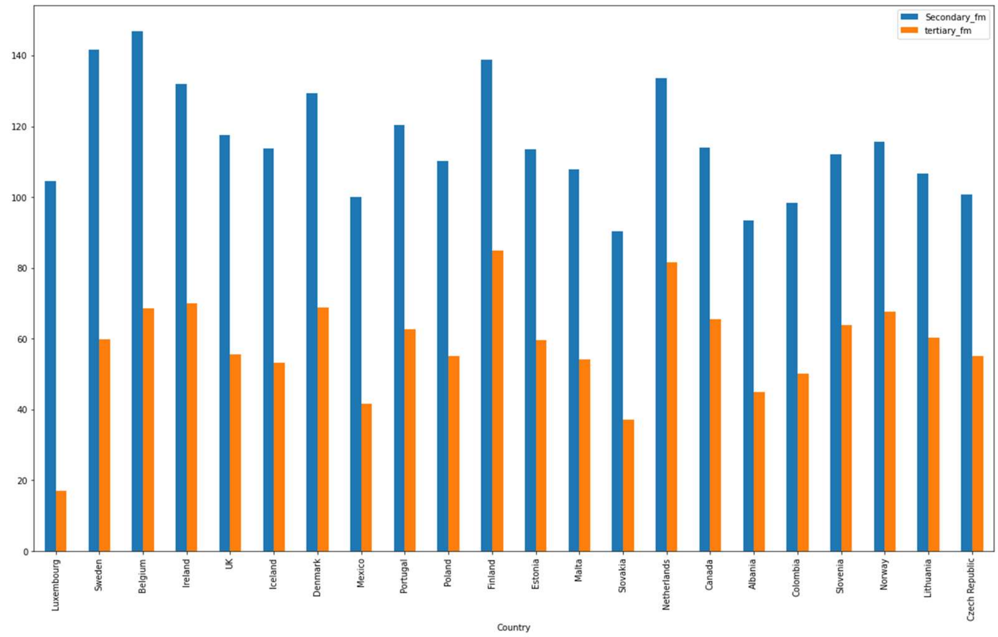

Figure 8 - Women education
(Source: Author)

4.2. Correlation Analysis

Spearman correlation coefficient was estimated to determine the association between variables of the dataset. Figure 9 shows a heatmap with a correlation matrix that contains the result of the performance Spearman correlation test in python using the dataset. The heatmap displays the coefficient of the correlation and indicates if there is a possible statistical significance for each combination of pair of variables (row and column), stronger colour means a stronger relationship. However, both variables can be influenced by other variables that drive a mathematical relationship. The heatmap allowed an easier identification of the relevant data to quickly discover the main correlations between the variables depicted in Figure 9, where the red colour means a negative relationship and the blue colour a positive relationship.

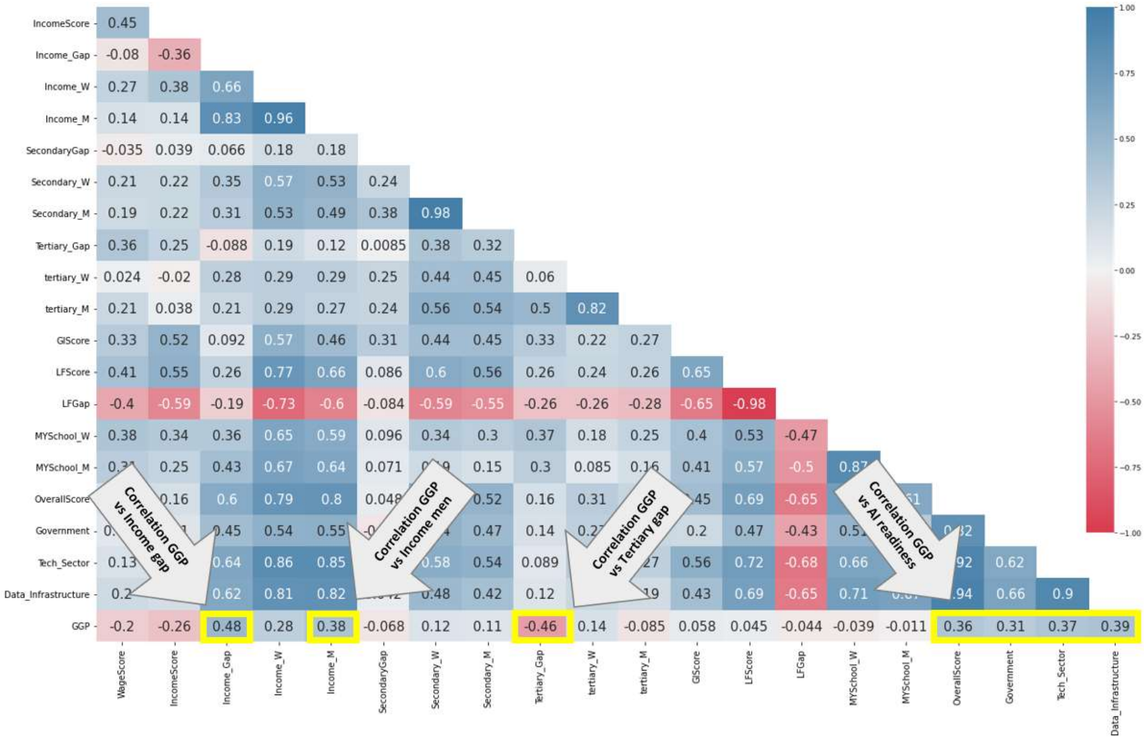

Figure 9 – Spearman Correlation Matrix
(Source: Author)

4.2.1. GGP Analysis

Figure 9 shows the Spearman correlation coefficient for each pair of variables. The last line of the matrix that contains the results for the correlation test for each numerical variable of the dataset and the GPP values. This information allows to identify what variables require to test the significance level (*p*), obtaining the depicted results in Table 2.

Table 2 - GGP Spearman's rho correlation
(Source: Author)

Test: Spearman's rho	
Variable	GGP
Income Gap	0.48***
Income Men	0.38*
Tertiary Education Gap	-0.46**
Government	0.31*
Tech Sector	0.37*
Data and Infraestructure	0.39**
*Significance levels: * p < 0.05, ** p =< 0.01, *** p=< 0.001*	

The p-value indicates there is a moderate correlation between GGP and the variables mentioned in Table 2. Furthermore, the p-value shows a statistically significant correlation mainly for the data and infrastructure and tech sector pillars. Thus, the AI readiness context in a country has a statistical correlation with the GPP, and it does not mean causation. However, the state of the technology sector and infrastructure could influence the GGP. Another important insight is that there is also a statistically significant correlation between the GGP and the income gap, as well as the tertiary gap and the GGP. In addition, the graphic representation of the correlation matrix between AI readiness variables and the GGP is illustrated in Figure 10. The scatterplots suggested a moderate positive correlation between GGP and AI readiness variables.

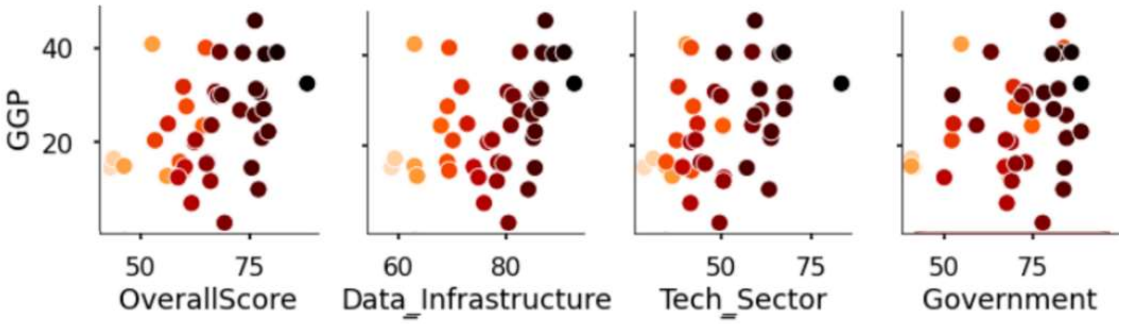

Figure 10 - AI readiness vs GGP
(Source: Author)

Figure 11 shows a tendency regarding GGP and the income gap with a positive correlation. The spread of the points in the scatterplot and the coefficient (r = .48, p = 0.001) confirm the level as moderate. Regarding tertiary education gender gap, the scatterplot shows a moderate and negative correlation with the GGP values. That corroborates the results obtained in the test (r = -.46, p < .01).

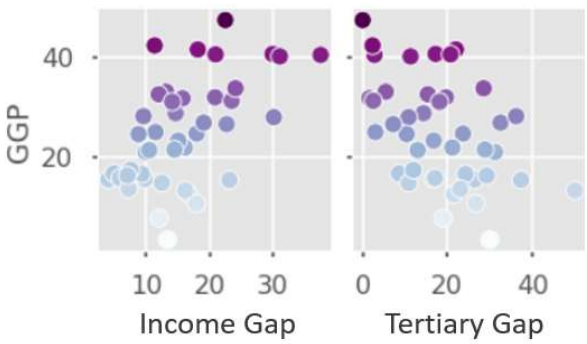

Figure 11 – GGP vs Income Gap and Tertiary Gap
(Source: Author)

4.3. GGP Multiple Linear Regression

Looking for an association between GPP and the other variables, a multiple linear regression analysis was completed using the GGP as a dependent variable and testing the other variables as predictors. From the analysis, several models were discarded, and the optimal model (Table 3) revealed income gap, tertiary education gap, mean years of schooling for women, and infrastructure pillar traits significantly predicted the GGP value. The model shows $R^2 = .527$, which is a good outcome, and adjusted R^2 at .475 that is satisfactory value. The regression results revealed that the predictors could estimate 52.7% of the GGP value variation, and the model coefficient (F-statistic) indicates it is not very likely it occurred by chance.

Table 3 - Model Summary[1]
(Source: Author)

Model	R-squared[a]	Adj. R-squared	F-statistic	Prob (F-statistic) [b]
OLS	0.527	0.475	10.29	1.06E-05***
a. Dependent variable GGP Predictors: (Constant), Income gap, Tertiary education gap, Mean years of schooling for women, Data and infrastructure pillar. b. Significance levels: *p <0.005, **p<0.01, *** p<0.001				

Table 4 – Coefficients [a]
(Source: Author)

Variable	Regression Coefficient(β)	Std error	t-statistic	p-value[b]
Constant	5.4558	3.807	1.433	0.16
Income gap	0.4834	0.207	2.34	0.025*
Tertiary education gap	-0.3254	0.123	-2.652	0.012*
Mean years of schooling for women	-2.7639	1.324	-2.087	0.044*
Data and infrastructure pillar	0.5601	0.24	2.331	0.025*
a: Depedent variable GGP *b: Significance levels: * p < 0.05, ** p =< 0.01, *** p=< 0.001*				

Table 4 describes the coefficients results from the model. The GGP as dependent variable was positively associated with infrastructure pillar ($\beta = 0.5601$, p-value<.05). Also, it indicates that the other variables statistically significant (p-value<.05) are the income gap ($\beta= 0.4834$), tertiary education gap ($\beta=-0.3254$), mean years of schooling for women ($\beta=-2.7639$). The four variables have significant participation to predict the variation of the GGP. The Section 4.2 shows some relationships between the independent variables. Although these relationships, the standard for concern about them required a correlation greater than .80 between two or more independent variables, then those relationships are not affecting the multicollinearity assumption.

[1] Appendix C

4.2.2. AI readiness and its relationship with other factors

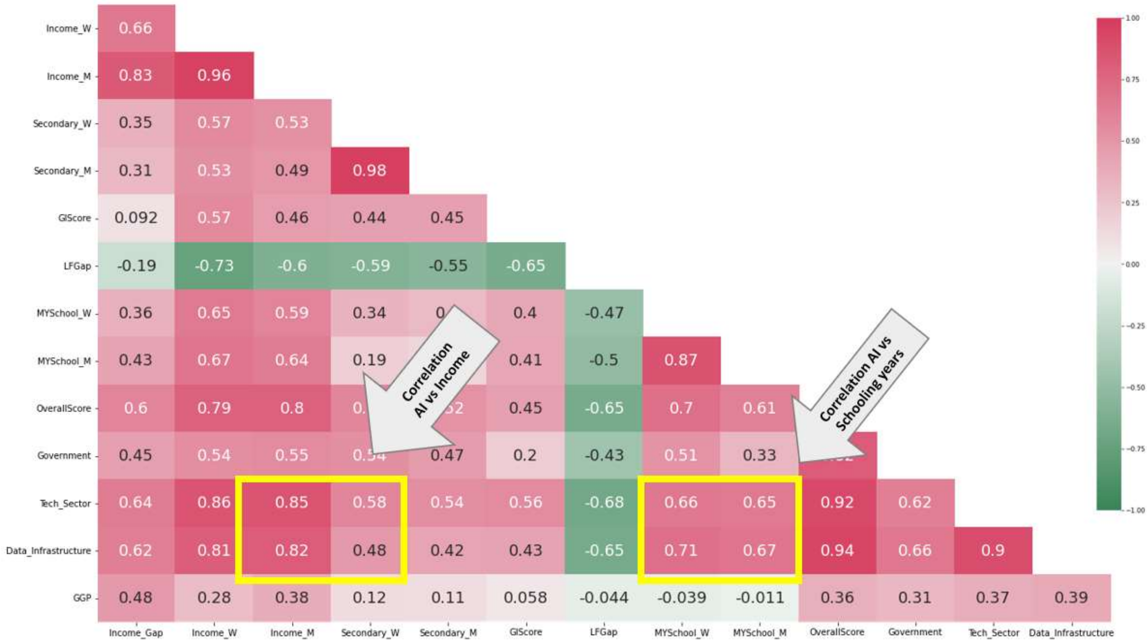

Figure 12 – AI Spearman matrix correlation
(Source: Author)

The heatmap in Figure 12 reveals a high correlation coefficient between the IA readiness indicators and the income variables. Also, it shows high coefficients for the correlation of the IA variables and years of schooling. The detail of the correlation and its significance levels is shown in Table 5. It shows the highest correlation for Data Infrastructure and Technology Sector with the income variables by gender. Results show Spearman's correlation test p-value < .001 for almost all combinations. Thus, there is a statistically significant correlation between AI readiness indicators and earnings for both genders.

Table 5 - AI readiness and Income variables
(Source: Author)

Test: Spearman's rho			
Variable	Income Gap	Income Women	Income Men
AI Overall Score	0.60***	0.79***	0-80***
Government	0.45**	0.54***	0.55***
Tech Sector	0.64***	0.86***	0.85***
Data and Infrastructure	0.62***	0.81***	0.82***
*Significance levels: * p < 0.05, ** p =< 0.01, *** p=< 0.001*			

The graphic representation of AI readiness global score and income variables confirms the results obtained with the coefficient and p-value of the test and shows stronger positive and linear correlations. Regarding government versus women income shows a graphic (Figure 13) that suggests a strong non-linear and monotonic correlation. On the contrary, tech sector and infrastructure revealed stronger positive correlations. The spread of points in the scatterplots for these variables suggests a stronger correlation.

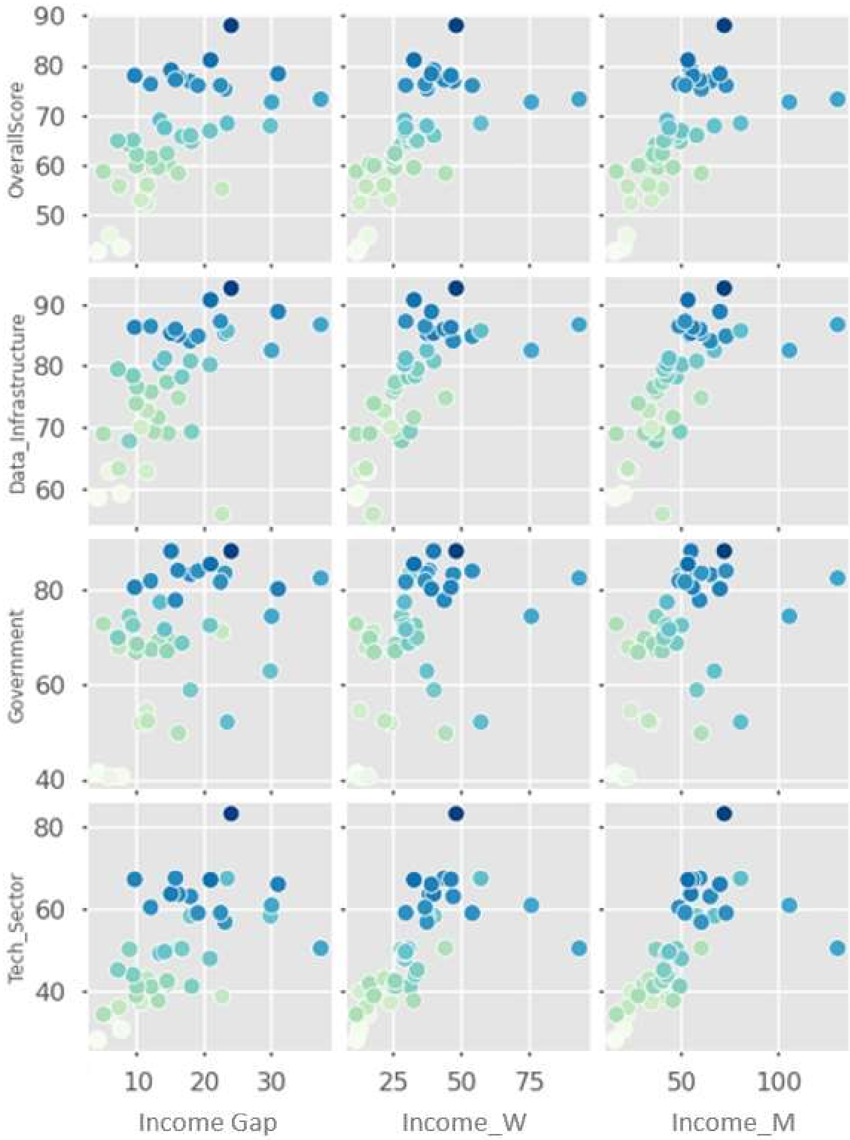

Figure 13 - Scatterplots AI vs Income variables
(Source: Author)

Regarding labour force gap, the analysis showed a negative correlation (r = -0.68, p-value = p < .001), which indicates a statistically significant correlation with tech sector pillar. Also, similar values were detected for the overall score (r = -0.65, p < .001), and infrastructure pillar versus labour force gap (r = -0.65, p < .001), for government pillar it revealed a less significative correlation (r = -0.43, p < .01) as is depicted in Figure 14, the spread for the other indicators also confirms a strong correlation.

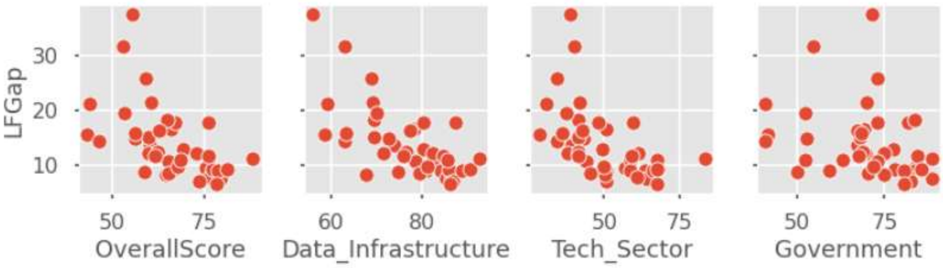

Figure 14 – Labour Force Gap vs AI readiness
(Source: Author)

Another important insight is the correlation between mean years of schooling for both genders and the infrastructure pillar. However, the stronger relationship was between income for women and infrastructure pillar (r = 0.71, p < .001) and similar values for tech sector pillar (r = 0.660, p < .001), in both cases there is a statistically significant correlation. In addition, Figure 15 suggests a non-linear correlation with the infrastructure and the tech sector pillars.

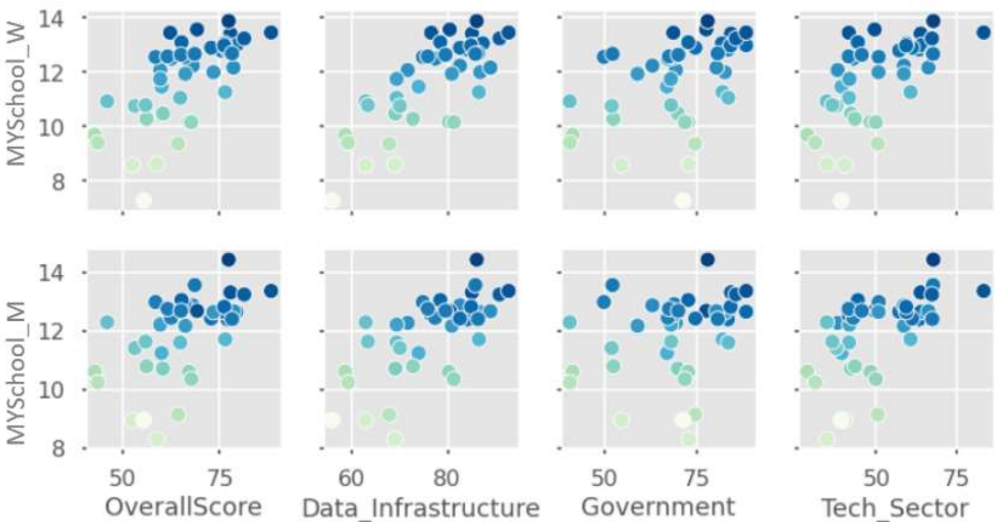

Figure 15 - Mean years of schooling vs AI readiness
(Source: Author)

4.4. Summary

To summarize, the descriptive analysis provided a clear status across the countries regarding gender disparity and AI readiness. AI tools and techniques such as heatmap and pair plots are practical for studying many variables at the same time and facilitate a visual interpretation of the results. The analysis correlation between AI readiness and education variables showed strong correlations. More precisely, the tech sector and infrastructure pillars showed a strong positive correlation with average years of schooling for both genders. For instance, when AI readiness increases are more likely that the mean years of schooling increase too. Multiple regression revealed that the most significant predictor for the GGP are the variables of education. It also confirmed the direction of the relationship direction found in Spearman's test. Both show a negative association between the GGP and the education variables. In the next section, the results are analysed in detail.

Chapter 5: Findings, Conclusions and Suggestions

The objective of the research is to provide insights into the role of AI and if it can help enhance women's retirement savings, measuring the statistical correlation between AI readiness and the gender gap pension. Additionally, the research sought to get insights into the association of AI readiness and factors that might influence GGP, such as education, workforce, and income. This section includes a review of the main findings and conclusions, limitations, and suggestions for further research.

5.1. Findings and discussion

The literature review indicates some countries are close to reaching parity for women in some sectors, whereas several countries still have a long route to cross to provide equality in pension (WEF, 2022; OECD, 2021c). The descriptive analysis details the latest GGP reported for the 42 economies, showing that in more than 20 countries, women earn 24.8% less pension income than men, and seven countries reported a GGP over 40%. The Global gender gap index indicates some countries are improving parity in few areas like labour force (WEF, 2022). However, descriptive analysis (Figure 7) revealed that some economies even with small labour force gap still need to strengthen efforts to reduce the gender gap in retirement savings. Another example is the education gap, the WEF (2022) indicated it is almost closed, and Figure 8 in descriptive analysis suggests that new area that needs to review closer is the gap between women enrolled in secondary and tertiary education because this gap is notable in several economies.

In addition, the literature review suggests there is a contrast between the countries leading the AI adoption and developing counties (EUC, 2020; Oxford Insights, 2019), and descriptive analysis confirmed it. Figure 3 shows the remarkable disparity between top countries and developing economies. Most countries considered for this study are trying to build capacity in the three pillars (EUC, 2020). However, according to the descriptive analysis, many economies require strengthening the tech sector pillar through building innovation capacity and a skilled labour force (Oxford insights, 2021). Furthermore, the literature review is plenty of use cases of deploy of AI, from basic chatbot, investment smart-advisors, to advance algorithms (Golić, 2019; Davenport, 2018; IFC, 2021). Although the solutions may overlap in some fields as FinTech and banking there are just few of them had been successfully implemented in pension sector (IOPS, 2018).

Regarding the first question about a relationship between the indicators of AI readiness and the GGP, the correlation analysis confirmed a moderate positive relationship, where the stronger relationship was with the data and infrastructure pillar. The Spearman test suggests when AI readiness rise, then it is expected to see a moderate increase in the GGP. The multiple regression indicates the GGP increases by .56 for each point increased in the infrastructure pillar. However, the relationship does not mean causation. According to the authors in section 2.2, many factors influence the GGP, and one with remarkable effect is the labour women conditions (Mavrikiou & Angelovska, 2020). Also, chapter two shows how several factors affect women's wealth accumulation and contributions to retirement savings (Prabhakar (2022), as well as access to opportunities to get a private pension plan (Dietz et al., 2003). In addition, UNESCO et al. (2022) point to AI can help address the challenges for women in the labour market. Answering the second part about potential AI-based solutions that could help reduce the GGP, the literature review (sections 2.3.2 and 2.3.3) demonstrates several examples of how AI reduces barriers and help face gender challenges. From robo-advisors, one-stop services, wealth management apps to complex insights to improve pension. AI provides solutions to detect and prevent gender bias in the labour market, improve parity by looking for fair salaries for women, ML algorithms to prevent school dropout, sentimental analysis, and gamification can improve women education, among others. Furthermore, AI solutions are facing poverty, decreasing gender disparity, and increasing people's wealth accumulation (WB, 2018; IRCAI, 2021; UNESCO et al., 2022).

To answer the second question regarding what other variables of the dataset have a relationship with the GGP is necessary to involve the main elements of this research: literature review, Spearman test, and multiple regression analysis. The multiple linear regression analysis revealed the infrastructure pillar, income gap, tertiary education gap, and mean years of schooling for women are significant variables that influence the GGP. Furthermore, from the AI readiness variables, the infrastructure pillar significantly influences GGP. According to the literature review, the income gender gap is one factor that prevents women from accumulating wealth (Holzmann et al., 2020) and directly affects the GGP. The correlation analysis indicated a relationship between the GGP and the income gender gap; its positive relationship suggests that if the income gender gap grows, GGP tends to increase. Also, the multiple regression analysis confirmed that the income gap is crucial to forecasting the GGP (Table 4). The multiple regression indicates that the GGP increases by 0.48 for each point that the gender income gap increases. Thus, aligned with the OECD (2021a), the analysis suggests that if women earn less than men, women are more likely to get lower benefits at retirement.

Regarding education, the Spearman test revealed a moderate negative relationship between the gender gap in tertiary-level and the GGP. The multiple regression analysis suggests that each point increased in the gender gap at the tertiary-level decreases the GGP by about 0.33. Thus, some countries are closing the gender gap in tertiary-level education and remain with high GGP due to the variables moving in the opposite direction. However, aligned with the insights of Nolan et al. (2019), the multiple regression revealed the positive influence of women's education on the GGP. Each year of education for women correlates with a decrease in GPP of around 2.76 units. Furthermore, the literature suggests education for women brings crucial benefits, including better pension, steady and long careers (Holzmann et al., 2020), and less risk of falling into poverty; as Clements et al. (2014) pointed out, higher education is equal to lower poverty rates. Finally, AI showed a strong positive correlation with mean years of education, potentially related to the high demand for technological skills in the labour market (UNESCO et al., 2022). Thus, AI is boosting the need for education, and at the same time, each year of women's education can help decrease the GGP.

Concerning the third question about the correlation between the indicators of AI readiness and other gender gap factors such as the labour force gap and the women's income, the analysis indicated correlations statistically significant. AI readiness shows a negative correlation with the labour force gap, that means for each increase of AI readiness the labour force gap decrease. Furthermore, literature suggests that several countries are looking to build capacity for AI adoption, including human talent (WEF, 2022). As Hupfer (2020) mentioned, the AI adopters are looking for a new skilled workforce. Thus, AI adoption tends to increase opportunities for skilled workers (Economics frontier, 2018), including women. Even when women are less likely to be prepared and work in STEM areas (UNESCO et al., 2022), the analysis confirmed a statistical relationship between AI readiness and the labour force gap. In addition, the results showed AI readiness is correlated with the income gender gap; but also showed a strong positive relationship between it and women's and men's income. Thereby when AI readiness grows, it is very likely to observe an income increase for both genders and build up the wage gender gap. Therefore, AI deployment generates new labour offers (Economics frontier, 2018) and opens more job opportunities for both genders and options to increase their income. Then, to complement the answer to the first question, the literature and the empirical evidence suggests that AI can impact crucial factors like the labour gap and women's income. Thus, AI can help improve women's retirement savings and reduce the GGP by addressing labour obstacles, reaching income parity, and enhancing women's wealth accumulation.

5.2. Conclusions

First, this research is the first empirical analysis that tests the correlation between AI readiness and the gender gap in retirement savings. This research provides meaningful insights regarding AI readiness and the GGP that can be used as a basis for further studies. Second, the literature review offered an extensive overview of AI solutions that are helping to face poverty, increase financial solutions, and reach gender equality. Above all, the literature review demonstrates how AI solutions can change the labour market, improving the conditions for women and tackling gender disparity in pension.

Third, the fact that the multiple regression model can explain more than 50% of the GGP with only four predictors shows the importance of using AI and ML techniques to study this area; it also opens a possibility to forecast the GGP for other countries for further research. The model provided meaningful information for understanding the relationship between the GGP, AI, and other factors. For instance, the considerable influence of women's schooling years on the GGP. Also, it revealed the complexity of the GGP, such as the negative relationship between the gap in tertiary-level education and the interaction between AI readiness, women's education, and GGP.

Fourth, the literature review and the statistical analysis confirmed that AI impacts factors linked with the GGP, such as income, education, and labour force gap. Thus, AI can influence them to change the GGP dynamics. Also, AI can provide meaningful insights and tools to study and address gender inequality in retirement savings. Finally, AI can improve the labour market conditions for women and reduce the GPP. However, closing the gender pension gap requires an understanding of the women's working life challenges and potentially closing other gender gaps, such as the pay gap. Women need opportunities to access the resources that can enhance their retirement savings, such as upskills, financial and digital literacy, better income, and policies to drive changes.

5.3. Limitations

The GGP is widely studied in Europe and established a standard methodology and source to measure it. Nevertheless, the current formal measure of GGP is only available for a few countries, and some regions have no available data. Outside of Europe, just a few OECD members collect the data needed to calculate it. Furthermore, the literature regarding AI deployment in the pension sector is still limited. It was not possible to find statistical research on the influence of AI and retirement savings, nor on the role of AI in the gender gap in pensions. Many studies exploring AI influence in the financial sector by solid literature reviews but do not show a standardized method to statistically measure the AI role.

5.4. Suggestions for Further Research

It is required to promote an international and standardized measure of the GGP. This work is essential to address this limitation in future global research to build a reliable machine learning model and explore what other factors are determining the pension gap to decrease gender disparity. Further research is necessary because the heatmap showed correlations between income, education, and the labour force gap. Also, new research can examine in detail the relationship between education, GGP, and AI because the study found that different education variables drive the GGP in different directions, and AI showed a notable impact on education for both genders. Further research might compare, for example, education in STEM areas and its relations with GGP and other GGP drivers, like the gender pay gap. Furthermore, more research with qualitative and quantitative data is needed to understand the potential and role of AI in pensions and GGP. Research could explore the AI role in the pension sector, including empirical data regarding the current operation of AI solutions and how it might enhance retirement savings or how AI can enhance saving using behavioural insights.