The Impact of Water Scarcity on Heath and Well-Being in Egypt

by

Dr. Rania Alaa Eldin Ahmed Khedr

Assistant Professor of Economics
School of Business and Economics,
Badr University in Cairo-BUC, Egypt
Rania.alaa@buc.edu.eg

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Abstract

This research aimed to study the impact of water scarcity on health and well-being in Egypt using two quantitative studies. In the first study, ARIMA model was used to model and predict two indicators of health and well-being by examining the effect of annual freshwater withdrawals, water productivity, and level of water stress as three indicators of water scarcity, beside population as a controlled variable. The results indicated that life expectancy at birth is positively affected by annual freshwater withdrawals and water productivity, while it is negatively affected by level of water stress and population. In contrast, the results of morality rate-under five were in stark contrast. In light of this, the two indicators of health and well-being in Egypt were predicted until 2030. In the second study, questionnaires were collected from a non- probabilistic sample of 407 individuals. The results indicated that difficulty (physical health problems) are not statistically affected by any the three dimensions of water scarcity, namely awareness, perception, and adaption/behavior, Frequency (psychological health problems) are positively and statistically affected by the three dimensions of water scarcity. Hence, the research came out a set of recommendations that help in treating water scarcity in Egypt in addition to support health and well-being of the Egyptian citizen. The research is considered an attempt to enrich studies that dealt with the relationship between the two variables in that it combined two quantitative studies. The research also suggested a set of future research opportunities when discussing the research limitations.

Keywords: Water scarcity; Health and well-being; Quantitative analysis; Egypt.

Introduction:

Water is vital for good hygiene and sanitation, both of which are critical to human health. As a result, water serves a variety of purposes in the body, especially the body uses water to replenish lost water through sweat and urine output. Water scarcity (closely related to water stress or water crisis) is the lack of fresh water resources to meet the standard water demand (Caretta et al., 2022).

Good health and well-being is one of the 17 Sustainable Development Goals established by the United Nations in 2015. The official wording is: “to ensure healthy lives and promote well-being for all at all ages”. This goal is the Sustainable Goal 3 (SDG 3 or Global Goal 3) (United Nations, 2015). Health is a state of complete physical, mental, and social well-being and not merely the absence of disease or infirmity (WHO, 2024). Well-being or welfare is what is ultimately good for a person, including everything considered valuable for them. It is a measure of how well a person`s life is going for them, both in a positive and a negative sense (Crisp, 2021). In its positive sense, well-being is sometimes contrasted with ill-being as its opposite (Headey, Holmstrom, Wearing, 1984).

Causes of disease that reside in human drinking water, such as bacteria, viruses, protozoa, and parasites, are the source of waterborne illnesses (WHO/UNICEF, 2014). Many of these illnesses result in gastrointestinal issues, such as diarrhea. This demonstrates that people's health is at danger when they don't consume enough water, both in terms of quantity and quality (Hannemann, 2015). Mor & Griffith (2011) point out that the second largest cause of disease burden in developing nations is diarrhea, which is caused by inadequate water quality and a lack of basic sanitation. Dehydration, which can be fatal, can result from the body having insufficient water (Hannemann, 2015). Furthermore, because water is essential to the human body's healthy operation, it is significant to evaluate water scarcity not only in terms of the quantity of water but also in terms of its quality (World Health Organization, 2011).

In Egypt, the 2021 UNICEF report confirms that the issue of water scarcity has been taken very seriously for years as a major challenge now and in the years to come. Egypt faces an annual water deficit of more than seven billion cubic meters, and this deficit is increasing annually, and Egypt may run out of water in the coming years (United Nations Children`s Fund – UNICEF, 2024). The WHO (2011) dedicated that non-communicate diseases, including cardiovascular diseases, diabetes, cancer, and chronic respiratory diseases, are the main cause of death in general and premature deaths in Egypt. However, with the increase in the water scarcity crisis in Egypt, this may be accompanied by the risk of death by infectious diseases as well.

Accordingly, this research aimed to study the impact of water scarcity on wealth and well-being in Egypt using two quantitative studies, the first study was based ARIMA analysis of published data on the two variables, and the second study was based on the statistical analysis of questionnaire data including the two variables.

First: Literature Review:

The researcher discusses the literature review related to the research according to the following order: water scarcity, health and well-being, and finally the relationship between the two variables.

1- Water Scarcity:

Water scarcity is defined as the quantitative abundance or lack of fresh water resources in general, and it may be primarily caused by humans (The CEO Water Mandate, 2014). As previously mentioned, water scarcity is associated with the terms water stress and water crisis.

The Food and Agriculture Organization (FAO) defines water stress as symptoms of water scarcity or shortage, which may include competition and conflict between water users, deterioration of reliability and service standards, harvest failure, and food insecurity (Food and Agriculture Organization of the United Nations - FAO, 2012). The CEO Water Initiative - an initiative of the United Nations Global Compact, defined it as including aspects of water availability, accessibility and quality. Accessibility is related to infrastructure, and it depends on whether or not customers can afford water (CEO Water Mandate, 2014). Kummu et al (2016) defined it as the impact of high water use, whether by withdrawal or consumption relative to water availability, thus it means that water stress would be a demand-driven scarcity.

Water crisis, also called water shortage, refers to the state of the world's water resources relative to human demand. The term has been applied to the state of water worldwide by the United Nations and other international organizations. The main aspects of water crisis are scarcity of water suitable for human use and water pollution (Intergovernmental Panel on Climate Change, 2008).

The CEO Water Mandate (2014) proposed unifying the four concepts (water scarcity, water stress, water crisis, and water shortage), noting that these terms shouldn`t be used interchangeably.

Experts have identified two types of water scarcity. The first is physical water scarcity, and the second is economic water scarcity. These terms were first defined in a study conducted by the International Water Management Institute (IWMI) in 2007. This study examined agricultural water use over the past 50 years to see if the world has enough water resources to feed a growing population in the future. The IWMI study was preceded by a study in the same field by Vorosmarty (2000).

Physical water scarcity occurs when natural water resources are insufficient to meet all demands or forms of demand for water. This includes water needed for ecosystems to function properly. Dry regions often suffer from physical water scarcity. Human impacts on climate have increased physical water scarcity in areas where this type of scarcity was already a problem (IPCC report, 2022). Physical water scarcity can also occur where natural water resources appear to be abundant but are overused for purposes such as infrastructure development, poor irrigation, energy generation, or urban expansion. Areas with desert climates such as Central Asia and North Africa often suffer from physical water scarcity (Rijsberman, 2006). Symptoms of physical water scarcity include declining groundwater, severe environmental degradation, and the allocation of water to some groups within a country at the expense of others (Food and Agriculture Organization of the United Nations – FAO, 2012). The United Nations Development Programme states that about one-fifth of the world's population lives in areas affected by physical water scarcity (United Nations Development Programme, 2006).

Economic water scarcity is due to a lack of investment in the infrastructure or technology needed to draw water from rivers, aquifers, or other natural water sources. Economic water scarcity may also reflect the insufficient human capacity of the water sector to meet the population's demand for water for various purposes (Portner et al., 2022, 551- 712). This may force people to travel or move long distances to fetch water for household or agricultural uses, and this water is often unclean. The United Nations Development Programme states that economic water scarcity is the most common cause or type of water scarcity, because most countries have enough water to meet household, agricultural, industrial, and environmental needs, but they lack the means, technology, or human capacity to provide it. The programme adds that about a quarter of the world's population is affected by economic water scarcity (United Nations Development Programme, 2006). Economic water scarcity is a feature of most sub-Saharan African countries, so improving water infrastructure and technology could help reduce poverty thereby increasing food production in these low-yielding areas, as well as improving public health (Faye and Carlos, 2012; International Water Management Institute – IWMI,2007; Ndalahwa, 2003).

Some academics prefer to add a third type of water scarcity, ecological water scarcity, which focuses on the demand for water for environmental purposes and refers to the minimum quantity and quality of water discharges needed to maintain sustainable ecosystems (Liu, Cao, Zhao, Lui, Lui, 2022). Some reports argue that this type is simply part of the definition of physical water scarcity (Food and Agriculture Organization of the United Nations – FAO, 2017).

The most common quantitative indicators (based on time series analysis) for measuring water scarcity are:

A- Annual freshwater withdrawals, total (billion cubic meters): it refers to total water withdrawals, not counting evaporation losses from storage basins. Withdrawals also include water from desalination plants in countries where they are a significant source. Withdrawals can exceed 100 percent of total renewable resources where extraction from nonrenewable aquifers or desalination plants is considerable or where there is significant water reuse. This indicator includes withdrawals for agriculture (total withdrawals for irrigation and livestock production), and industry (total withdrawals for direct industrial use such as withdrawals for cooling thermoelectric plants), withdrawals for domestic uses, and withdrawals for municipal use or supply and use for public services.

B- Water productivity, total (constant 2015 US$ GDP per cubic meter of total freshwater withdrawal): Water productivity is calculated as GDP in constant prices divided by annual total water withdrawal. It refers to the amount of economic output or value created per unit of water utilized in a specific activity or process. It gauges how well water resources are used to generate products or services.

C- Level of water stress: freshwater withdrawal as a proportion of available freshwater resources is the ratio between total freshwater withdrawn by all major sectors and total renewable freshwater resources, after taking into account environmental water requirements. Main sectors, as defined by ISIC standards, include agriculture; forestry and fishing; manufacturing; electricity industry; and services. This indicator is also known as water withdrawal intensity.

From a micro-analysis perspective (citizen level) and using a qualitative study based on personal interviews with citizens and farmers in two villages in South Africa, Lolwana (2017) identified seven dimensions of water scarcity:

A- Perceptions about water service delivery: It assesses aspects such as lack of water quantity, low quality, and high price.

B- Views about reasons for water shortage: It assesses aspects such as lack of rainfall, drought, weak water infrastructure, weak capacity to treat and desalinate water, and ill-considered expansions.

C- Experiences of drinking water: It assesses aspects such as experiences of low quality drinking water, or its smell turning bad or changing its color for the worse, or causing diseases such as stomach aches or physical itching.

D- Challenges experienced due to water scarcity: It assesses aspects such as lack of water use for personal purposes, shrinking green spaces, high prices for water-based services, and the cessation or decrease in production of some industries or agriculture.

E- Ways to communicate challenges: It evaluates the methods used by citizens to communicate their concerns about water scarcity to the relevant authorities such as the media, social media, etc.

F- Level of community participation: It evaluates aspects such as the participation of citizens and local communities with the relevant authorities in solving the problem of water scarcity.

G- Suggestions to address challenges: It evaluates aspects such as the relevant authorities changing the water ratios between governorates and regions, recycling and treating wastewater, and taking strict measures to prevent water pollution.

From another micro-analysis perspective, and using a qualitative study based on the questionnaire method with farmers, the study of Rezaei, Salmani, Razaghi, and Keshavarz (2017) identified three dimensions of water scarcity, which are:

A- Awareness: It refers to the interest in environmental problems. In other words, an aware person understands the risks and difficulties resulting from any environmental problem and knows that he may suffer from the consequences of this environmental problem. Therefore, he is concerned about it. When there is an environmental problem such as water scarcity, awareness will increase and improve a person's understanding of it. A citizen may be aware of the problem of water scarcity because it may affect his health and perhaps his life and a farmer may be aware of this problem because it may affect agricultural productivity.

B- Perception: Perception is the next stage of awareness. Perception refers to a person's certainty of the existence of the problem of water scarcity, its current and future risks, his awareness of its causes, and its repercussions in the form of a decrease in its quality and the diseases resulting from it, in addition to its high prices.

C- Adoption or behavior: Adaptation or behavior is the next stage of awareness. Sufficient awareness of the problem of water scarcity may turn into multiple adaptive behaviors such as reducing the amount of water used for various purposes, and resorting to purchasing mineral or bottled water.

The three previous dimensions were identified based on the Theory of Planned Behavior designed by Ajzen (1985), which explains how awareness is transformed into intention and then into behavior or action. The researcher uses these three dimensions in the qualitative analysis of the current study.

Water is a finite resource. However, water scarcity is a relative concept as the amount of water that can actually be obtained varies with changing supply and demand. Water can become scarce for a number of reasons, including a shortage of water for various reasons; demand for water exceeds supply, inadequate water infrastructure, or institutions failing to balance the needs of society. Water scarcity is a growing problem on every continent, but it is disproportionately affecting poorer communities, who are less resilient to climate change and growing populations (United Nations- UN WATER, 2024).

Climate change is making water scarcity more difficult, as climate change makes water supply less predictable, and the storage of water on land – the water in soil, snow and ice – is diminishing as the climate changes; this disrupts community activity (United Nations Children`s Fund - UNICEF, 2024).

There are also many studies conducted on the causes or determinants of water scarcity. Chowdhary, Bharagava, Mishra, and Khan (2020) reported that many sources are responsible for water pollution and scarcity, such as industrial wastewater, domestic sewage, storm water runoff, and agriculture practices. Out of which, industries play a key role and also release various toxic chemicals, organic and inorganic matters, sulfur, asbestos, acids, etc. These wastes when discharged into the water ecosystem without adequate treatment become very unhealthy for any type of human and other use. The industrial wastewater is responsible for many diseases such as anemia, low blood platelets, headaches, risk for cancer, many skin diseases, etc. To prevent such type of issues, the study recommended the use of effective treatment technology, water reuse, desalination, repair and maintenance of infrastructure, and stricter and proper implementation of environmental and water pollution control laws.

Kumar et al (2020) indicated that rapid global changes (climate change, population growth, and urban expansion) had cumulatively affected the major river systems. Particularly, communities in isolated riverine islands are heavily affected due to their poor adaptive capacities. The focal point for the vulnerability of these people lied in the water resources (drinking water availability, salt-water intrusion, flooding, etc.). Therefore, the poor adaptive behaviors of residents living near these areas reduced their well-being. This paper advocated the socio-hydrological research in the context of enhancing social adaptive capacity as well as developing resilient water.

Zakar, Zakar, and Fischer (2020) theoretically confirmed that the impact of climate change on scarcity might differ fundamentally between countries. Climate change might reduce the capacity of the government to provide health care to the population. Water scarcity means not only availability but also the quality of water. Developing countries will be mainly affected by water scarcity due to the increase in their population, which will disrupt their health care systems. Despite the role of climate change, it is not the only reason for water scarcity, but there are also wrong policies for governments, improper distribution of water within the country, and political conflicts.

Integrated water management is largely capable of dealing with water scarcity effectively. This integrated management provides information on monitoring water supply and demand at the overall level of the country and each region separately. It is also able to provide green and hybrid water, especially for the needs of agriculture and industry. It tries to explore groundwater, which is part of the solution, protect it and use it sustainably. It has measures to reduce losses resulting from poor water distribution, reuses wastewater in a safe manner, and desalinates water, in addition to using citizen awareness practices to reduce water use in homes and encourages citizens to adopt sustainable diets (World Bank, Water Resources Management, 2022).

Blignuant and Van Heerden (2009) found that South Africa is experiencing a water scarcity crisis due to climate change, increased water demand and the presence of dangerous plant species. The study confirmed that the water scarcity crisis would negatively impact economic development initiatives in South Africa. The study recommended the use of sectoral water allocation by applying the general equilibrium model for comparative accounting of the macroeconomics using integrated databases that ensure social accounting and using sectoral water use budgets.

2- Health and Well-being:

Health has a variety of definitions, which have been used for different purposes over time. In general, it refers to physical and emotional well-being, especially that associated with normal functioning of the human body, absent of disease, pain (including mental pain), or injury. The concept of health has undergone significant transformation throughout history. Initially, definitions rooted in the biomedical model emphasized the body's capacity to function, viewing health as a state of normalcy that could be intermittently disrupted by illness. A representative definition from this era describes health as a state characterized by anatomic, physiologic, and psychological integrity; the ability to perform personally valued family, work, and community roles; and the capacity to manage physical, biological, psychological, and social stress (Stokes; Noren; Shindell, 1982). In 1948, however, the World Health Organization (WHO) introduced a groundbreaking definition that expanded the notion of health to encompass well-being, articulating it as physical, mental, and social well-being, and not merely the absence of disease and infirmity (World Health Organization, 1958). While this definition was embraced by some as a progressive shift, it faced criticism for its vagueness and lack of measurability. Consequently, it was often regarded as an impractical ideal, with discussions of health frequently reverting to the more tangible biomedical model.

Well-being, often referred to as wellness, prudential value, prosperity, or quality of life, represents that which holds intrinsic value for an individual. Therefore, the well-being of a person encompasses what is fundamentally beneficial for that individual, aligning with their self-interest (Crisp, 2017).

As a common division, health and well-being can be divided into five components, which may be interrelated, but each contributes in its way to a better life. To stay and life well, all these components must be look after. The five components are: physical, emotional, intellectual, social, and spiritual.

The most common quantitative indicators (based on time series analysis) for measuring health and well-being are:

A- Life expectancy at birth, total (years): Life expectancy at birth indicates the number of years a newborn infant would live if prevailing patterns of mortality at the time of its birth were to stay the same throughout its life.

B- Mortality rate, under-5 (per 1,000 live births): Under-five mortality rate is the probability per 1,000 that a newborn baby will die before reaching age five, if subject to age-specific mortality rates of the specified year.

C- Prevalence of HIV, total (%of population ages 15-49): Prevalence of HIV refers to the percentage of people ages 15-49 that are infected with Human Immunodeficiency Virus.

D- Incidence of tuberculosis (per 100,000 people): Incidence of tuberculosis is the estimated number of new and relapse tuberculosis cases arising in a given year, expressed as the rate per 100,000 population. All forms of TB are included, including cases in people living with HIV. Estimates for all years are recalculated as new information becomes available and techniques are refined, so they may differ from those published previously.

E- Maternal mortality ratio (modeled estimate, per 100,000 live births): Maternal mortality ratio is the number of women who die from pregnancy-related causes while pregnant or within 42 days of pregnancy termination per 100,000 live births. The data are estimated with a regression model using information on the proportion of maternal deaths among non-AIDS deaths in women ages 15-49, fertility, birth attendants, and GDP measured using purchasing power parities (PPPs).

From a micro-analysis perspective (citizen level), Vries et al (2016) argued that quantitative measures of health-related well-being may not capture relevant aspects of well-being such as physical pain and psychological aspects such as anxiety and depression in humans. Therefore, Vries and his colleagues suggest that these measures should be replaced by comprehensive measures for health-related well-being, in order to improve assessments related to health economics, or that both quantitative and descriptive measures should be taken into account when assessing health-related well-being in order to improve the quality of the measurement. In line with the WHO definition, the Delphi technique showed that measuring well-being related to health, should take into account both mental and social dimensions in humans. For this purpose, Vries et al (2016) designed a questionnaire consisting of 56 statements that initially measure 21 dimensions of health-related subjective well-being (HR-SWB). This scale was tested on an expanded sample of 1143 individuals and dimensional analysis was used to arrive at the smallest number of latent factors. Using Exploratory Factor Analysis (EFA), a five-factor or dimensional scale of health-related subjective well-being was proposed. These dimensions are:

A. Physical independence: It assesses a person's ability during a specific past period of time to perform important daily activities and take care of himself, in addition to the absence of physical pain or physical health problems that prevent him from performing physical activities on his own.
B. Positive affect: It assesses a person's feelings during a specific past period of satisfaction, joy and happiness.
C. Negative affect: It assesses a person's feelings of surrender, helplessness, loneliness, anxiety, depression, and lack of a goal to live for.
D. Autonomy: It assesses a person's self-esteem in multiple aspects such as his confidence in his opinions and self-efficacy, his freedom to live his life and determine his own destiny, his ability to adapt to life's variables, his enjoyment of everything he owns and experiences, and his satisfaction with himself and the balance between his obligations and his pleasure.
E. Personal growth: It evaluates a person’s perspective on life in terms of it being a source of new experiences, continuous learning, growth, and transformation into a better person.

More recently, Brazier et al (2022) reported that existing measures of estimating life years are limited in their measurement; because they are mostly based on health-related quality of life, so Brazier and his colleagues developed a measure that includes both health and well-being, the EQ-HWB (EuroQol-Health and wellbeing). EuroQol is a Dutch non-profit research organization. The researchers developed this scale in four stages: first, the content or dimensions were identified through a review of qualitative literature based on a conceptual framework in the field of health economics, then items or statements covering this content or dimensions were generated and selected, then the face validity of these statements was tested using qualitative interviews with 168 individuals from patients, users of health care facilities, the general population, and caregivers in six countries (Argentina, Australia, China, Germany, the United Kingdom, and the United States of America). Extensive psychometric testing of the candidate statements (using classical methods, factor analysis, and item response theory) was conducted on a larger sample of 4000 respondents in the six countries indicated. This resulted in the design of the extended version of the EQ-HWB scale consisting of 25 statements related to three dimensions of health-related quality of life and well-being. This version achieved high reliability and validity in all countries indicated except China. The shortened version of the EQ-HWB, known as the EQ-HWB-S, includes nine statements that resulted from subsequent statistical analyses to design and generalize the use of the long version. These statements also relate to three dimensions of health-related quality of life and well-being. These dimensions are:

A. Difficulty: It assesses the problems related to physical health and well-being that a person has been exposed during a specific past period of time.
B. Frequency: It assesses the problems related to psychological health and well-being that a person has been exposed during a specific past period of time.
C. Severity: It assesses the severity of the problems related to either physical health and well-being or psychological health and well-being. Which a person has been exposed during a specific past period of time.

Brazier et al (2022) found that the EQ-HWB-S items correlated with other subjective measures of health, such as the EuroQuol Five-Dimensional Questionnaire (EQ-5D), or the HR-SWB scale, which was previously described and also includes five dimensions. However, the EQ-HWB-S attempted to integrate well-being alongside health.

3-Previous Studies that Addressed the Relationship between the Two Variables:

Nyemba, Manzungu, Masango, and Musasiwa (2010) assessed the extent of water scarcity at the household level and its resultant environmental impacts in Zimbabwe. The study was based on two separate surveys. The first survey examined the extent and impacts of water scarcity at household level, and data were collected through household questionnaire, interviews with specialists, medical records review, and physical observations. The second survey assessed microbial levels in the main water sources and was complemented by examining water-related disease profiles. Water scarcity was found to be more severe in low income than high income suburbs, due to unfair water distribution policies in the city that favored high income suburbs in terms of both quantity and quality of water, and the failure of low income suburbs residents to access safer water alternatives. Microbial assessment indicated presence of coliform in water obtained from the tap and alternative sources at levels above WHO. Water scarcity and low quality resulted in water-related diseases and environmental contamination.

Masaharu, Itsubo, and Inaba (2011) have modeled the assessment of health damage resulting from domestic water scarcity or poor quality of it, for a number of African countries using non- linear regression models. They found that domestic water scarcity or poor quality of it are strongly linked to health damage caused by infectious diseases such as diarrhea and jaundice. The study indicated that the desalination technologies of domestic water are expected to be a countermeasure to limit water stress and reduce health damage.

Abedin, Collins, Habiba, and Shaw (2019) used a questionnaire to investigate the impact of water scarcity on water resources and human health in two villages in southwestern coast of Bangladesh. The results showed that local community believed that climate change has significant impacts on freshwater resources and health. More than 70% of respondents identified diarrhea, dysentery, and skin diseases as the prime waterborne health risks that occur through climate change-related safe water scarcity. The study suggested some adaptive methods to deal with water scarcity.

Zenko and Menga (2019) study used qualitative analysis based on in-depth interviews in addition to published data. The results showed that water scarcity, successive water cuts, and the use of manufactured water are factors that negatively affected health and well-being of Lake Urmia Basin citizens in Iran in terms of chronic psychological stress, social isolation, intra-community conflicts, despair, hopelessness, depression, and anxiety.

Rosinger and Young (2020) study theoretically discussed the effects of possible water shortage or interruptions in homes, examining how these effects relate to human health and biology throughout the human life cycle. Based on a review of studies in human and animal models, the study indicated the potential effects of lack of water in homes, including diarrhea, dehydration, stunting, malnutrition, psychological stress, negative birth outcomes, impaired cognitive functions, high blood pressure, and chronic kidney disease. These effects will become more serious with age and with the advancement of generations. The study suggested conducting longitudinal studies on a country or group of countries, and cross-sectional studies to compare several countries at a specific time, the necessary evidence to prove a causal relationship.

Livingstone (2021) emphasized that water scarcity and pollution in many African countries pose health risks to both urban and non-urban areas in Africa. The study noted diseases associated with water scarcity and pollution in urban areas in some African countries, such as Ghana, Liberia, and Sierra Leone. These diseases include Ebola, cholera, and diarrhea. In Egypt, the study indicated that industrial water pollution led to chronic hepatitis and kidney inflammation in Tanta. The study also indicated that water pollution resulting from the industrial use of chemical fertilizers is transported to Cairo via the Nile River.

The study by Filho et al. (2022) emphasized that water scarcity threatens livelihoods, health, food systems, security, economies, ecosystems, and well-being in Africa, triggering a wide range of adaptive responses. This study reviewed 240 articles and identified the adaptive characteristics of planned and autonomous responses to water scarcity across Africa. The study showed that the adaptive responses to water scarcity of individuals and households are greater than the adaptive responses of governments and their institutions. At the individual level, women's adaptive responses to water scarcity are greater than men's. From a household income perspective, the relatively greater responses are for low-income households.

Using the quantitative method based on closed-ended personal interviews with a sample of 399 people in a district in Pakistan, Rassol, Saeed, Sharif, Khan, and Khan (2023) found that people feel frustrated and faced dangerous situations as a result of their lack of access to clean water sources. The study also indicated that most people are faced to travel in search of water, and there are problems among joint families and neighbors over the unjust allocation of water. Furthermore they are obliged to buy water, which had a negative impact on their financial situation. Women and children were disproportionately responsible for bringing water, which had a negative impact on their health and wellbeing.

Rhue et al (2023) conceptualize the social and health costs of household water insecurity for children. Diarrheal disease has historically been the primary cause of infant and child death in the global burden of disease linked to water insecurity. However, children are also negatively affected by unsafe or inadequate household water, both in terms of their health and social development. Rhue and his colleagues compile data on a wide range of health effects that affect kids from birth to late adolescence in four areas: exposure to contaminated or unsafe water; problems in growth due to inadequate hydration and nutrition; negative social consequences, including absenteeism from school and violence among peers; and additional non-communicable health conditions, including mental health, accidents, and reproductive health. The burden and urgency of these issues are linked to projected increases in water scarcity caused by climate and conflict, human displacement, and environmental pollution in the coming decades.

Zhu et al (2023) argued that in drylands water stress is a significant problem that typically results in unequal advancements in ecological, social, and economic systems. It is unknown, meanwhile, how it would affect drylands' ability to meet the Sustainable Development Goals (SDGs). This study evaluated water stress and its effects on sustainable development in Inner Mongolia, using partial correlation and multiple regression analyses performed for the water-related indicators and SDGs. Findings of the study imply that, despite Inner Mongolia's quick progress toward the SDGs, ignoring the progress's equity overestimates the current state of affairs and fails to take regional disparities into account. Uneven progress objectives have gotten worse as a result of the poor performance of many SDGs over the last few decades. The relationship between these issues and water resources has been further analyzed. Moreover, multiple SDGs related to human essential needs and environmental conservation, including SDG 1 (no poverty), SDG 2 (zero hunger), SDG 3 (good health and well-being), SDG 7 (affordable and clean energy), and SDG 12 (responsible consumption and production), were significantly positively correlated with ecological water consumption, whereas SDGs related to economic growth, such as SDG 8 (decent work and economic growth), were positively correlated with industrial water consumption. These results imply that the inconsistent progress across the SDGs might be explained by a conflict in water allocation for the accomplishment of several SDGs, which in turn hinders the sustainable development of these drylands.

Focusing on water quality testing facilities in Solapur district, Sheikh and Birjdar (2024) explored the impact of water quality on public health and well-being. The methodology used in this study combined qualitative and quantitative data collection techniques (Sargeant, 2012). Structured questionnaires were created and distributed to key stakeholders, such as community members, environmental agencies, and representatives of water quality testing laboratories in the district and subdivisions. The study emphasized the importance of water quality monitoring in the prevention of chronic and waterborne diseases, as it found a clear link between poor water quality and several health consequences. Community awareness and engagement initiatives are essential elements, empowering local residents to take an active role in water quality monitoring. Future directions include adopting new technologies, community empowerment initiatives, improving collaboration, and focusing on climate change adaptation. The study concludes by emphasizing the importance of water quality monitoring as a fundamental safeguard for community well-being and for proactively investing in a safer and healthier future.

Abanyie, Amuah, and Nang (2025) in their study investigated the intricate relationship between water scarcity and accessibility, and the associated implications on sanitation practices in Damongo, a newly created regional capital and an emerging city. The results of the questionnaire showed that the area faced evident water scarcity; with a daily per capita water consumption as low as 0.128 m3. Mechanized boreholes emerged as potential solutions, particularly for the 61.2% of respondents experiencing waiting times exceeding 15 min. The economic repercussions were noteworthy, as high water costs impacted livelihoods, especially for low-income households. Sanitation challenges are widespread, with 62.8% relying on pit latrines, and 56.1% lacking proper infrastructure. Water and sanitation-related diseases like typhoid and diarrhea highlight the need for urgent interventions to enhance water quality and sanitation practices. Gender imbalances persist in water-fetching responsibilities, with 58.2% relying solely on females. Domestic water sources predominantly involved traditional options, potentially exposing residents to unsafe practices. Sanitation maintenance practices and intervals varied, signaling the necessity for comprehensive solutions. Insights on the health dimension considered uncovering the prevalence of the top five water and sanitation-related diseases for 2022. These included typhoid, diarrhea, Cholera, Dysentery, and Hepatitis. These findings suggest the pressing need for improved sanitation and clean water access, as inadequate infrastructure and water scarcity contribute significantly to these health challenges.

Zimmermann et al (2025) elaborates from a panel discussion at the 2023 United Nations Water Conference on “Addressing Water Scarcity to Achieve Climate Resilience and Human Health.” Understanding and addressing water scarcity goes beyond hydrological water balances to also include societal and economic measures. study aims to examine five categories of health impacts resulting from deteriorating water quality and quantity: water-related diseases and water for hygiene; malnutrition and water for food, livelihoods, income, and development; water for energy; poor air quality from dust and wildfire smoke caused by drought; and mental health impacts from factors related to water scarcity. The discussion of barriers and opportunities for resilient water systems begins by reframing water scarcity as a "path to water bankruptcy" and introducing water partnerships to empower local water leaders with the awareness, education, and resources needed to develop and implement locally appropriate water management strategies. Other barriers include a lack of tools to consider the socioeconomic impacts of water scarcity, a lack of water-related information in formats actionable for decision-makers, a lack of clarity in applying water scarcity modeling to obtain policy-relevant results, and insufficient drought adaptation planning. The study provides recommendations for various stakeholders to address these barriers, most notably collaborative, multidisciplinary water partnerships, knowledge sharing in accessible formats, and enabling inclusive participation.

The analysis of the previous studies shows the following:

1- Most of the previous studies were conducted on a specific country, including Zimbabwe (Nyemba et al, 2010), Bangladesh (Abedin et al, 2019), Iran (Zenko and Menga, 2019), Pakistan (Rassol et al, 2023), Mongolia (Zhu et al, 2023), and India (Shaikh and Birajdar, 2024), Ghana (Abanyie, Amuah, and Nang, 2025). While some studies were conducted on a group of countries, such as some countries in Africa (Filho et al, 2022; Livingston, 2021; Masaharu et al, 2011).

2- The research methods used in the previous studies were varied. Most of the previous studies were theoretical studies that relied on the literature review (e.g. Filho et al, 2022; Rhue et al 2023; Rosinger and Young, 2020; Zimmermann et al., 2025). While some previous studies relied on qualitative analysis using personal interviews (Rassol et al, 2023; Zenko and Menga, 2019). Some previous studies used the quantitative method based on the questionnaire and surveys (Abanyie, Amuah, and Nang, 2025; Abedin et al, 2019; Shaikh and Birajdar, 2024; Nyemba et al, 2010). Other previous studies also used the quantitative method but relied on the correlation and regression analyses (Masaharu et al, 2011; Zhu et al, 2023).

3- Previous studies have addressed some demographic variables that had a significant impact on health and well-being as a dependent variable. These variables are: income (Filho et al., 2022; Nyemba et al., 2010), population (Brazier et al., 2022; Kumar et al., 2020), age (Rhue et al., 2023; Rosinger and Young, 2020), gender (Abanyie et al., 2025; Filho et al., 2022; Rassol et al., 2023), governorate (Abanyie et al., 2025; Abedin et al., 2019; Livingston, 2021; Rassol et al., 2023; Zenko and Menga, 2019).

Accordingly, the research gap is that no previous study, to the best of the researcher`s knowledge, has examined the impact of water scarcity on health and well-being in Egypt in an in-depth quantitative study, and no previous study has examined this impact using two quantitative analysis methods. The current study addresses this research gap, so the current research uses two quantitative studies, The first is based on time series analysis, using GDP per capita and population as two controlled variables, and the second study is based on questionnaire data analysis, using gender, income, and governorate as three demographic variables.

Second: The Research Problem:

Water scarcity is a global crisis, about 4 billion people, or nearly two-thirds of the world's population, suffer from severe water scarcity for at least one month a year (Mekonnen & Hoekstra, 2016), about 10% of the world's population, or about 720 million people, live in countries experiencing high and critical levels of water stress in 2021, with children and women being the most affected groups, and about 1.2 billion people, or about one-sixth of the world's population, live in agricultural areas that suffer from severe water shortages or scarcity, according to the Food and Agriculture Organization of the United Nations - FAO, 2020. (United Nations- UN WATER, 2024).

Drinking contaminated water can lead to a number of infectious disorders in people. As a result, these illnesses create a population that is ill and unable to work to support their development. The availability of portable, clean water significantly improves a community's health (WHO, 2012). Accordingly, (Motoshita, Itsubo, & Inaba, 2011) highlights that water scarcity in many regions of the world leads to inadequate access to safe drinking water, which can cause infectious diseases like typhoid and salmonellosis to spread through fecal contamination of drinking water. Accordingly, WHO (2014) contends that in addition to harming people's health, a lack of water or water of low quality also reduces a community's and individual's ability to develop effective resistance against a variety of health risks Elliott (2011) states that the fact that 1.4 million children die from diarrhea each year can be used to gauge the significance of water in maintaining human survival. Additionally, one in five children born in impoverished nations will not live to be five years old due to contaminated water (Elliott, 2011).

The 2021 UNICEF report shows that around 1.8 billion people around the world will live with absolute water scarcity. Climate change is a major part or cause of the problem. These climate changes are having devastating effects on the health and well-being of children worldwide, with 920 million children – more than a third of all children worldwide – currently experiencing severe water scarcity. Children are more vulnerable and less able to withstand the shocks associated with water scarcity, such as droughts and heat waves, than adults, and they are physiologically more susceptible to diseases caused by toxic substances such as lead and other forms of pollution found in untreated or improperly treated water used for drinking and agriculture, although adults are more susceptible to psychological disorders associated with water scarcity and poor quality, such as fear, anxiety and despair about the future (United Nations Children’s Fund – UNICEF, 2021).

Regarding Egypt, Egypt pays the utmost attention to the issue of water, whether in terms of preserving and managing its water resources well or defending its historical rights to the Nile water, the main water supplier, which has been translated into many comprehensive and specific legal agreements, with the Nile Basin countries. In return, Egypt cooperates with the Nile Basin countries and participates in many of their development projects. The most important agreements are: the 1959 Convention, under which Egypt obtains 55.5 billion cubic meters of water annually, and the 2015 Declaration of Principles agreement between Egypt, Sudan and Ethiopia, in Khartoum, which affirmed joint cooperation on the basis of understanding, benefit and gains for all and the principles of international law, and understanding the water needs of upstream and downstream countries in their various aspects (State Information Service, 16 June 2022).

Egypt current water resources are as follows: The River Nile, it is the main source of water in Egypt, with Egypt's share of 55.5 billion cubic meters of water, representing 79.3% of water resources and covering 95% of current water needs, the groundwater, the amount of groundwater used in Egypt is estimated at about 6.1 billion cubic meters/year in the Valley and the Delta, the rain, but it is not a major source of water because of the lack of quantities that fall in winter, as about 1.3 billion cubic meters of rainwater fall on Egypt every year, reuse of agricultural wastewater, it is one of the most significant water sources, where the annual average of agricultural wastewater is about 12 billion cubic meters/ year, about 5.7 billion cubic meters are currently reused, and the treated wastewater, it can be used for irrigation purposes provided that it meets the internationally recognized health conditions, as its quantity is about 2.5 billion cubic meters per year, about 1.3 billion cubic meters of which are reused after being treated in desert land farming projects. In contrast, the total water needs in Egypt amount to about 114 billion cubic meters of water annually (Heggy et al., 2021). The agricultural use of water represents the largest part of water uses, reaching about 65.61 billion cubic meters of total uses in 2017/2018. The needs of the industrial sector from water were estimated at about 4.5 billion cubic meters in 2018, as for the uses of drinking water and sanitation purposes, it is estimated at 75.10 billion cubic meters, according to the bulletin of the Central Agency for Public Mobilization and Statistics in 2019. The average loss of pure drinking water is estimated at 9.27% of the total water at the level of the republic is lost in dilapidated networks, houses, schools and government agencies. (Aziz et al., 2019).

Many studies discussed the water challenges facing Egypt (e.g., Aziz et al., 2019; Beyene et al., 2010; Heggy et al., 2021), the most important challenges facing Egypt are population growth, as it is a major challenge for water resources, the total population in Egypt is expected to reach more than 175 million people in 2050, which is a great pressure on water resources, climate change also is a major challenge, and the Ethiopian Renaissance. According to the opinions of experts, the risks of the Renaissance Dam are as follows:

1- Reducing Egypt's water share by 20 billion cubic meters of Nile water, which constitutes a disaster for Egypt, if it occurs, as a result of the destruction that will affect agriculture and livestock and stop development projects in it, in addition to the destructive environmental effects and drought, which may push the region to enter into military conflicts over water or what is known as water wars.

2- If the Renaissance Dam project is completed and the starts of storage years, this will lead to a decrease in Egypt's share of water by 9 to 12 billion cubic meters per year. If Ethiopia decides to build an integrated dam group (four dams), this will lead to an increase in the shortage of Egypt's share of water by 15 billion cubic meters annually, in addition to losing about 3 million acres of agricultural land and displacing 5 to 6 million farmers. There is a possibility that the collapse of the dam will occur as a result of its construction in a sloping area that witnesses the rush of the Blue Nile water of more than half a billion cubic meters per day, which is water that descends from places with high heights of up to 2000 meters, which may cause massive floods that may overthrow some villages and cities. But in the event of a complete collapse, the huge rush of water held behind the dam will cause the flooding of many cities and may be completely flooded and Khartoum will be among these cities, as a result of the collapse and destruction of the Al-Rosarous, Sinar and Marwa dams located within the Sudanese borders.

3- It is expected that the period of filling the reservoir of the Renaissance dam will last 6 years, accompanied by a deficit in hydropower production in

Egypt in addition to the decrease in the level of Lake Nasser to about 15 meters, in addition to periods of drought and deterioration in water quality.

Based on the above, the water crisis is one of the biggest and most serious challenges facing Egypt as it is a crisis related to Egyptian national security and the future of future generations.

From other side, there are a lot of health problems resulting from lack of water; the lack of usable water pushes people to resort to contaminated water full of dangerous germs to meet their needs. Nearly one million people die annually from diseases related to water pollution by sewage or other pollutants. Lack of water can indirectly affect human physical health due to the fact that groups of people around the world have to carry water on their backs and shoulders for long distances to deliver it to their homes or places of use, and women are the group most affected by this process because of the physical stress it causes and affects its health in the event of pregnancy and the health of the fetus as well. Children are among the groups most affected by lack of access to safe drinking water. Pure water is essential for proper development and it also protects children from the transmission of diseases to them through contaminated water, such as typhoid. Diarrhea is also one of the diseases resulting from water pollution. It is one of the 3 most important causes of child death in the world. In the world, there is a child who dies every two minutes due to diseases transmitted by contaminated water, or because of diarrhea that causes dryness in the child's body. There are about 160 million children around the world suffering from stunting diseases and malnutrition directly related to the lack of drinking water or the lack of sanitation services that prevent water pollution. (The world economic forum water initiative, 2011; Nadal, 2015).

All of the above confirms the importance of the water scarcity crisis in terms of its impact on health and well-being. This is what the researcher mentioned when commenting on the previous studies about the scarcity of previous studies that examined the impact of water scarcity on health and well-being in Egypt. Therefore, the current study attempts to answer the following question: does water scarcity affect health and well-being in Egypt?

Third: The Research Objectives:

The research aimed to:

1- Review the literature on water scarcity, health and well-being, and the relationship between them.
2- Measure the impact of water scarcity on health and well-being in Egypt using two quantitative studies, and discuss the results reached.
3- Provide recommendations to help the Egyptian government in facing the water scarcity crisis and improving the health and well-being of the Egyptian citizen.
4- Provide recommendations for future research in light of the results and limitations of the current research.

Fourth: The Research Method:

Balog (2020) asserted that economic research has always applied both quantitative and qualitative methods ever since it came into being. Research in Economics, especially in Microeconomics remained much more qualified than in other social research.

Quantitative and qualitative methods represent two different approaches and paradigms in respect to scientific research. Quantitative methods, which depend on numerical data such as published quantitative data and closed questionnaire are necessary to build up models and theories and they aim to objectivity. Qualitative methods, which depend on interviews, observations and open questionnaires to some extent, are necessary to justify generalizability through testing models and theories and they are aware of subjectivity (Cameron et al., 2019; Hanson et al., 2019).

Balog (2020) indicated the importance of mixed researches which use both qualitative and qualitative method together in order to benefit from the advantages of each approach.

However, in line with the research trend in economics, the researcher used quantitative methods, relying on two studies, one of which used time series analysis and the second used closed questionnaire data analysis.

1-The First Study:

Initially, three indicators were used to measure water scarcity – as an independent variable, namely: annual freshwater withdrawals, water productivity, and level of water stress. Also, five indicators were used to measure health and well-being – as a dependent variable, namely: life expectancy at birth, mortality rate, under-5 (per 1,000 live birth, prevalence of HIV, total (% of population ages 15-49), Incidence of tuberculosis (per 100,000 people), and maternal mortality ratio (modeled estimate, per 100,000 live births). Two controlled variables were used, GDP per capita and total population. GDP per capita (measured by current U.S. dollars) is gross domestic product divided by midyear population. GDP is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without making deductions for depreciation of fabricated assets or for depletion and degradation of natural resources. Total population or population is based on the de facto definition of population, which counts all residents regardless of legal status or citizenship.

However, it came to light that the EViews program treats all the indicators of the independent variable and the controlled variables as independent variables, and does not recognize the concept of control variables. Due to this constraint, GDP and population must be represented as independent variables in the model. Despite this constraint, the research proceeded, with adjustments made to ensure the model`s of robustness and accuracy. GDP was found to have an adverse impact on model performance. This was demonstrated by a drop in indices that analyze the ARIMA model`s performance. The deletion indicated that GDP could be removed from the model, resulting in a significant increase in its efficiency. This revised model better fitted the data, resulting in more accurate and robust predictions. Also, prevalence of HIV, total (% of population ages 15-49), incidence of tuberculosis (per 100,000 people), maternal mortality ratio (modeled estimate, per 100,000 live births) as three dependent variables were removed for the same reason, and because their time series data did not correspond to the length of the key independent and other dependent variables employed in the research. Specially, the time series for these three removed dependent variables were shorter than those for other variables, thus they were excluded from the research.

The research used 49 observations from 1975 to 2023 to model and forecast life expectancy at birth and mortality rate in children under five years, by examining the effect of annual freshwater withdrawals, water productivity, water stress levels, and population on life expectancy at birth and mortality rate in children under-5 using Autoregressive models. The Sample World Development Indicators release provided data for all the research variables from 1975 to 2023.

Time series data is evaluated using several statistical models, including autoregressive (AR), moving average (MA), and autoregressive integrated moving average (ARIMA), which combine the two. The Box-Jenkins technique has gained popularity. This technique relies on inputs from models such as moving average (MA), integrated (I), and autoregressive (AR). This technique also differentiates non-stationary databases until they become stationary. Before running ARIMA (autoregressive integrated moving average), the Augmented Dickey-Fuller Generalized Least Squares used for more robustness and ensuring that data was stationary. Models are identified using AIC and BIC. AIC (Akaike Information Criterion) is aimed at finding the best approximating model to the unknown data generating process whilst BIC (Bayesian Information Criterion) is designed to identify the true model. AIC does not depend directly on sample size (Acquah, 2010). Bozdogan (1987) noted that because of this, AIC lacks criterion properties of asymptotic consistency. After estimating the model's parameters using Maximum Likelihood Estimation, perform diagnostic tests with EViews program. Forecasts are produced if the model is acceptable; otherwise, alternative models should be considered (Bheemanna & Budihal, 2023).

The researcher explains below the results of the quantitative analysis and discusses these results.

A- Graphical Representation of Research Variables Data:

Fig. 1 below demonstrates the data of the independent variables from 1975 to 2023 and shows that there was an increase in annual freshwater withdrawals during the study period (1975-2023) with fluctuations. The same is true for water productivity, but in 2017 there was a decrease in water productivity followed by another increase in the following periods. Water stress levels showed a significant increase from 1975 to 1999, followed by a decrease in 2000, and then another increase. As for population, there was a continuous increase throughout the study period. These results suggest that water demand has increased significantly during the study period which may lead to severe water scarcity in Egypt.

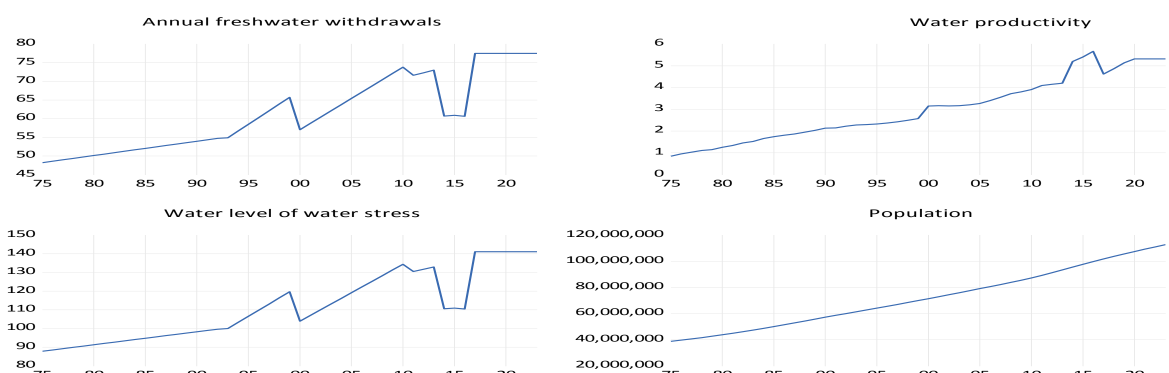


Fig. 1: The data of the independent variables from 1975 to 2023

Fig. 2 below demonstrates the data of the dependent variables from 1975 to 2023 and shows that life expectancy at birth has increased significantly from 1975 to 2010. From 2011 to 2023, the increase continued but with fluctuations. Regarding the mortality rate for children under five years, it has decreased during the study period (1975–2023). From 2000 to 2023, the decrease was significant but with fluctuation. These results indicate an improvement in healthcare, nutrition, and living conditions, and other variables contribute to health. The time series' rising and downward behavioral patterns of the two dependent variables indicate that some of its features may not be stationary. The two time series show diverse average values and fluctuations in different sub periods.

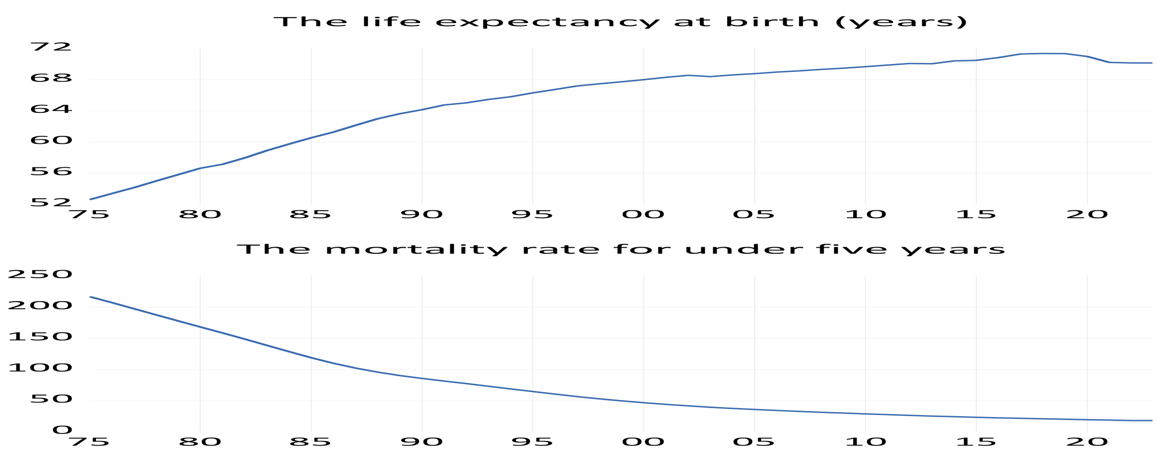
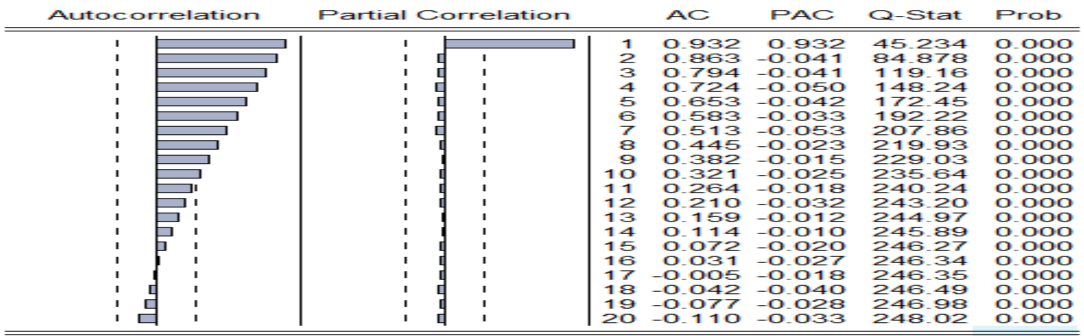


Fig. 2: The data of the dependent variables from 1975 to 2023

B-Stationary of the series and Model Identification:

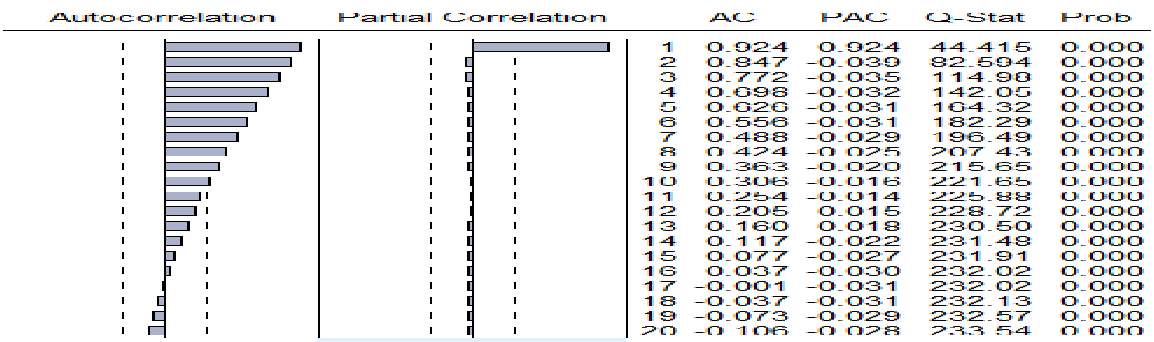
A statistical series is considered stationary if it's mean, variance, and covariance do not fluctuate or change over time.

To test stationary, the researcher used the correlogram. A correlogram of the series displaying the autocorrelation function (ACF) for 20 lags for these two variables is shown in Figs. 3 and 4.



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.932	0.932	45.234	0.000
		2	0.863	-0.041	84.878	0.000
		3	0.794	-0.041	119.16	0.000
		4	0.724	-0.050	148.24	0.000
		5	0.653	-0.042	172.45	0.000
		6	0.583	-0.033	192.22	0.000
		7	0.513	-0.053	207.86	0.000
		8	0.445	-0.023	219.93	0.000
		9	0.382	-0.015	229.03	0.000
		10	0.321	-0.025	235.64	0.000
		11	0.264	-0.018	240.24	0.000
		12	0.210	-0.032	243.20	0.000
		13	0.159	-0.012	244.97	0.000
		14	0.114	-0.010	245.89	0.000
		15	0.072	-0.020	246.27	0.000
		16	0.031	-0.027	246.34	0.000
		17	-0.005	-0.018	246.35	0.000
		18	-0.042	-0.040	246.49	0.000
		19	-0.077	-0.028	246.98	0.000
		20	-0.110	-0.033	248.02	0.000

Fig. 1 Correlogram of the life expectancy at birth



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.924	0.924	44.415	0.000
		2	0.847	-0.039	82.594	0.000
		3	0.772	-0.035	114.98	0.000
		4	0.698	-0.032	142.05	0.000
		5	0.626	-0.031	164.32	0.000
		6	0.556	-0.031	182.29	0.000
		7	0.488	-0.029	196.49	0.000
		8	0.424	-0.025	207.43	0.000
		9	0.363	-0.020	215.65	0.000
		10	0.306	-0.016	221.65	0.000
		11	0.254	-0.014	225.88	0.000
		12	0.205	-0.015	228.72	0.000
		13	0.160	-0.018	230.50	0.000
		14	0.117	-0.022	231.48	0.000
		15	0.077	-0.027	231.91	0.000
		16	0.037	-0.030	232.02	0.000
		17	-0.001	-0.031	232.02	0.000
		18	-0.037	-0.031	232.13	0.000
		19	-0.073	-0.029	232.57	0.000
		20	-0.106	-0.028	233.54	0.000

Fig. 2 Correlogram **of the mortality rate for under five years**

The series displays non-stationarity due to a strong correlation coefficient of 0.932 and 0.924 for both life expectancy at birth and mortality rate-under five years. Autocorrelation Function (ACF) values steadily declines, and the series displays a well-defined autocorrelation even with many lags.

Also, Augmented Dickey-Fuller (ADF) test was used to examine the stationary of the series (Cheung and Lai, 1995; Gianfreda, Maranzano, Parisio, and Pelagatti, 2023). This test examines the null hypothesis that a unit root is present in a time series sample. The results of this test are given in Table 1.

Table 1: Augmented Dickey-Fuller unit root test

The dependent variables	At level		At first difference	
	ADF	P-value	ADF	P-value
The life expectancy at birth	-2.186	0.21	-6.93	0.00
The mortality rate for under five years	-1.027	0.74	-7.47	0.00

The ADF test results indicate that the series is non-stationary of the life expectancy at birth and mortality rate for under five years at level as the p values obtained are greater than the significance level of 0.05. The Box-Jenkins technique cannot be used if the time series is non-stationary (Hamjah, 2014). To become stationary, the series must be transformed by differing the origin series. The first difference was taken for two variables, and the ADF test results were less than the significance level of 0.05, indicating that the two series became stationary.

Based on the observations above, below are the proposed ARIMA models: The ARIMA (1, 1, 1) model is adequate for both the life expectancy at birth and the mortality rate for under five years. This model consists of an autoregressive component (AR (1)) and a moving average component (MA (1)), with differencing used to attain stationarity. (ARIMA 1,1,1) refers to a specific type of autoregressive integrated moving average model used in time forecasting). The AIC and BIC are then used to find the best ARIMA parameters (p, d, q) for the life expectancy at birth and the mortality rate for under five years. A nonseasonal ARIMA model is classified as an ARIMA (p,d,q) model, where: p is the number of autoregressive terms, d is the number nonseasonal differences needed for stationarity, and q is the number of lagged forecast efforts in the prediction equation (Asteriou and Hall, 2011; Milles, 1990).

C-Modeling and Forecasting of the Life Expectancy at Birth (years)

Table 2 shows the significant parameters ($p<0.01$) for the ARIMA (1,1,1) model.

Table 2: Estimation results of the ARIMA model of the life expectancy at birth

Parameters	Coefficient	Std. Error	t-Statistic	Prob.
C	0.35	0.28	1.24	0.22
AR (1)	0.95	0.09	10.92	0.00
MA (1)	-0.39	0.17	-2.38	0.02
SIGMASQ	0.04	0.01	5.64	0.00
R-squared	0.70	Mean dependent var		0.37
Adjusted R-squared	0.68	S.D. dependent var		0.36
S.E. of regression	0.20	Akaike info criterion (AIC)		-0.23
Sum squared resid	1.88	Schwarz criterion (BIC)		-0.08
Log likelihood	9.66	Hannan-Quinn criter.		-0.17
F-statistic	34.81	Durbin-Watson stat		1.94
Prob(F-statistic)	0.00			
Inverted AR Roots	0.95			
Inverted MA Roots	0.39			

The ARIMA (1,1,1) model can be written as**:** $\boldsymbol{\Delta L y_t = \mu + \emptyset y_{t-1} + \theta e_{t-1} + e_t}$ **(1)**

While ΔL represents the differencing operator applied to the data. It indicates the difference between consecutive observations, which is required to ensure that the series remains stationary. y_t denotes the value of the time series at time (t)., μ denotes the intercept term, $\emptyset$denotes the AR coefficient, θ denotes the MA coefficient, and e_t denotes the residual or error term. The fitted ARIMA (1,1,1) model is: (Akın et al., 2021)

ΔL life expectancy at birth =0.35−0.95y_{t-1} $-$ $0.39e_{t-1} + e_t$ (2)

The model coefficients't statistic and P value indicate significant parameter estimates for all explanatory variables at a level of 0.01 and the Constant coefficient (C) of 0.35 indicates a non considerable baseline effect on life expectancy at birth. The Estimated parameters of the ARIMA model were done using like Maximum Likelihood Estimation (MLE) methods. SIGMASQ (Variance of the Error Term) has a coefficient of 0.04 with a p-value of 0.00 suggesting a good fit between the model and the data. The mean value of 0.37 indicates that, on average, the dependent variable has a value of 0.37 over the period covered by your data.

The overall model is statistically significant, as demonstrated by the F-statistic value of 34.81 and the p-value of 0.00. The AR (1) term is significant, indicating that past values of life expectancy effect current values, and the MA (1) term is also significant, implying that earlier errors affect current values. That's with Inverted AR Roots and Inverted MA Roots of 0.95 and 0.39 respectively indicating that there is stability in the autoregressive process and in the moving average process. And the R-squared is 0.70 is good. And with low values of All three criteria (AIC, BIC, Hannan-Quinn criteria) which indicates that this model is the best. The model's standard error of regression is 0.20. Sum Squared Residuals of 1.88, which is the total deviation of the observed values from the fitted values. The log likelihood is 9.66, that's all indicate the model's goodness of fitness. As the best one among the evaluated models, ARIMA (1,1,1) was tested in autocorrelation and heteroscedasticity. Durbin-Watson D statistic was found to be 1.94, very close to 2.000, which means that there is no autocorrelation problem.

To test the heteroscedasticity case of the ARIMA (1,1,1), was found the most suitable model for the time series transformed logarithmically. The obtained new model's coefficients were significant with p- value <0.05. Figure 5 shows the results of fitting the model to the life expectancy at birth (years) data. The solid line represents the actual data, while the upper and lower dotted lines represent the model's fitted values and residuals, respectively.

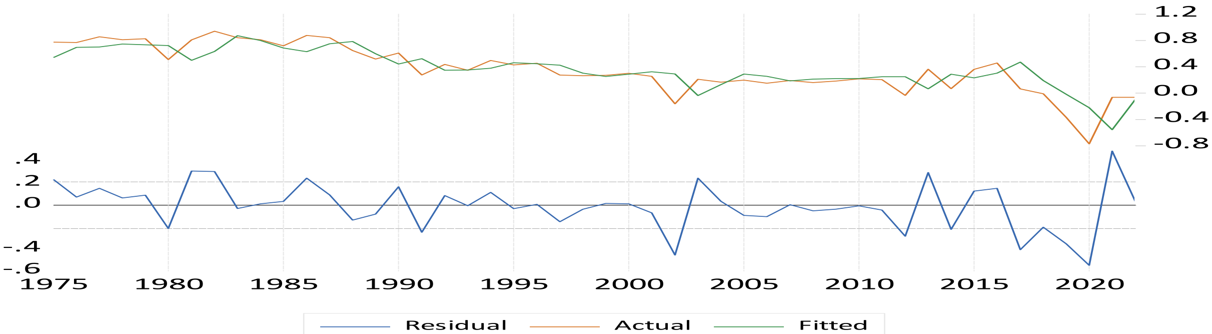
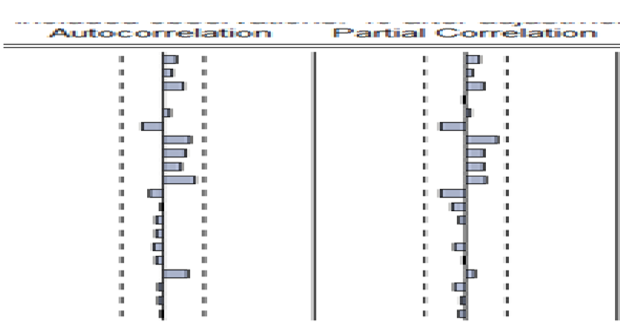


Fig. 3 Actual series, fitted series and residual series of the life expectancy at birth (years) sequence

After fitting the ARIMA (1, 1, 1) model, the residual is tested for white noise. Figure 6 shows the autocorrelation and partial autocorrelation function graphs for the residual series. The residual is white noise, which indicates that the model is valid.



	AC	PAC	Q-Stat	Prob
1	0.095	0.095	0.4672	0.494
2	0.070	0.062	0.7284	0.695
3	0.142	0.131	1.8209	0.610
4	0.014	-0.014	1.8322	0.767
5	0.062	0.047	2.0501	0.842
6	-0.126	-0.159	2.9789	0.811
7	0.196	0.228	5.2572	0.629
8	0.167	0.135	6.9670	0.540
9	0.123	0.132	7.9195	0.542
10	0.232	0.150	11.356	0.330
11	-0.083	-0.171	11.805	0.378
12	-0.001	-0.088	11.806	0.461
13	-0.035	-0.035	11.893	0.536
14	-0.043	0.006	12.024	0.604
15	-0.051	-0.069	12.218	0.662
16	-0.040	-0.014	12.342	0.720
17	0.182	0.066	14.927	0.601
18	-0.031	-0.082	15.003	0.662
19	-0.028	-0.029	15.067	0.718
20	-0.012	-0.036	15.080	0.772

Fig. 4 The residual series' autocorrelation and partial autocorrelation function plots

The ARIMA (1,1,1) model was used for forecasting life expectancy at birth (years) between 2024 and 2030, utilizing a dynamic forecast mode with results listed in Table 3. The results revealed an excellent fit between the actual and fitted values, indicating an important effect on future life expectancy at birth.

Table 3: life expectancy at birth (years) forecasts for the period 2024-2030

Year	2024	2025	2026	2027	2028	2029	2030
Forecasted	70.1	69.9	69.8	69.7	69.6	69.6	69.5

Table.3 shows that the forecasts indicated that the life expectancy at birth (years) would drop from 70.145 to 69.5 The updated life expectancy at birth (years) for 2024 has not been published by the World Development Indicators.

For diagnostic tests, The Jarque-Bera Test and The ARCH test of heteroskedasticity. Conclude that the residuals follow normal distribution and there is no heteroskedasticity in the residuals, as indicated by a p-value of 0.53, and 0.89, respectively.

The next step is to Estimate the Effect of Independent Variables on the life expectancy at birth. Table 4 shows the correlation matrix between independent variables and life expectancy at birth.

Table 4: Correlation matrix between independent variables and life expectancy at birth.

Variables	**Life expectancy at birth (years)**	**Annual freshwater withdrawals**	**Water productivity**	**Level of water stress**	**Population**
Life expectancy at birth (years)	**1**				
Annual freshwater withdrawals	**0.380**	**1.000**			
Water productivity	**0.451**	**0.133**	**1.000**		
Level of water stress	**-0.479**	**0.041**	**-0.127**	**1.000**	
Population	**-0.849**	**-0.094**	**-0.259**	**-0.064**	**1.000**

As demonstrated in the correlation matrix, there is no correlation above 0.85 between independent variables for all variables included in the analysis(Wheeler & Tiefelsdorf, 2005).

Table5 shows the estimation of the effect of Independent variables on the life expectancy at birth

Table 6: Estimation of the effect of independent variables on the life expectancy at birth

Variables and parameters	Coefficient	Std. Error	t-Statistic	Prob.	VIF
C	1.25	0.12	10.71	0.00	
Annual freshwater withdrawals	0.97	0.18	5.43	0.00	1.8
Water productivity	0.04	0.01	3.79	0.00	2.1
Level of water stress	-0.74	0.05	-14.58	0.00	2.3
population	-1.27E-08	1.43E-09	-8.90	0.00	1.4
AR (1)	0.45	0.20	2.26	0.03	2.2
MA (1)	0.59	0.16	3.71	0.00	2.8
SIGMASQ	0.005	0.001	4.84	0.00	1.3
R-squared	0.96	Mean dependent var		0.37	
Adjusted R-squared	0.96	S.D. dependent var		0.36	
S.E. of regression	0.07	Akaike info criterion (AIC)		-2.21	
Sum squared resid	0.22	Schwarz criterion (BIC)		-1.90	
Log likelihood	62.22	Hannan-Quinn criter.		-2.10	
F-statistic	159.04	Durbin-Watson stat		1.80	
Prob(F-statistic)	0.00				
Inverted AR Roots	0.45				
Inverted MA Roots	-0.59				

The full model can be expressed as follows:

ΔL Life expectancy at birth (years) = 1.25 + 0.97* Annual freshwater withdrawals + 0.04* water productivity -0.74* water level of water stress - 1.27E-08* population + $0.45y_{t-1} + 0.59e_{t-1} + e_t$ (3)

The model coefficients' t statistic and P value indicate significant parameter and coefficients estimates for all explanatory variables at a level of

0.01. The Estimated parameters of the ARIMA model were done using like Maximum Likelihood Estimation (MLE) methods. SIGMASQ (Variance of the Error Term) coefficient is 0.005 with p- value of 0.00. It ensures that the residuals behave appropriately and that the model does not overfit the data.

The overall model is statistically significant, as demonstrated by the F-statistic value of 159.04 and the p-value of 0.00. The AR (1) term is significant, indicating that past values of life expectancy effect current values, and the MA (1) term is also significant, implying that earlier errors affect current values. That's with Inverted AR Roots and Inverted MA Roots of 0.45 and -0.59 respectively indicating that there is stability in the autoregressive process and in the moving average process. And the high R-squared and adjusted R-squared values (both 0.96) indicates that the model explains a large proportion of the variation in life expectancy at birth. And with low values of all three criteria (AIC, BIC, Hannan-Quinn criteria) which indicates that this model is the best. The model's standard error of regression is 0.07 and Sum Squared Residuals of 0.22, which is the total eviation of the observed values from the fitted values. With the log likelihood is 62.22, all indicate the model's goodness of fitness. As the best one among the evaluated models, ARIMA (1,1,1) was tested in autocorrelation and heteroscedasticity. Durbin-Watson D statistic was found to be 1.8, very close to 2.0, which means that there is no autocorrelation problem.

The coefficient of the constant (c) is 1.25 indicates a considerable baseline effect on life expectancy at birth (years). The annual freshwater withdrawal coefficient is 0.97, indicates that each increase in annual freshwater withdrawal by 100% leads to an increase in life expectancy by 97%. Water productivity coefficient is 0.04, indicates that each increase in water productivity by 100% leads to an increse in life expectancy by 4%. Water stress coefficient is -0.74, indicates that each increase in water stress by 100% leads to a decrease in life expectancy by 74%. Population coefficient is -1.27E-08, indicates that each increase in population by 100% leads to a decrease in life expectancy by 1.27E-08%.

To test the heteroscedasticity case of the ARIMA (1,1,1), was found to be the most suitable model for the time series transformed logarithmically. The obtained new model's coefficients were significant with p- value <0.01. Figure 7 shows the results of fitting the model to the Estimated Model. The solid line represents the actual data, while the upper and lower dotted lines represent the model's fitted values and residuals, respectively.

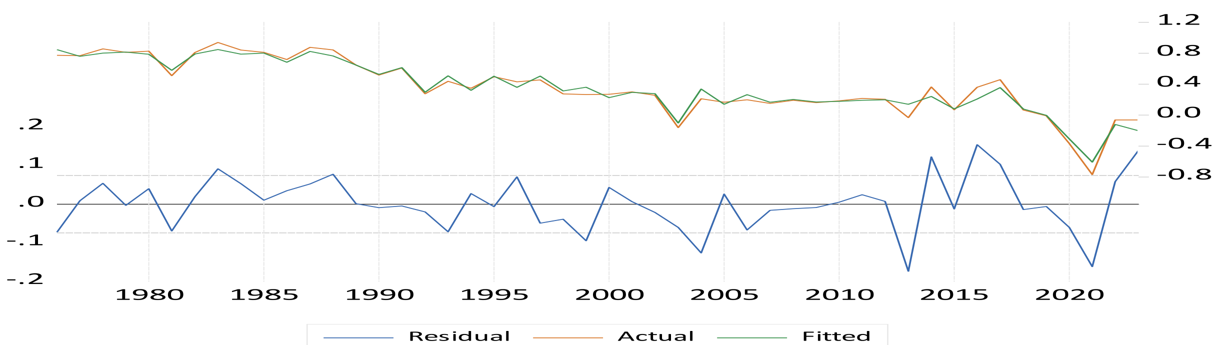
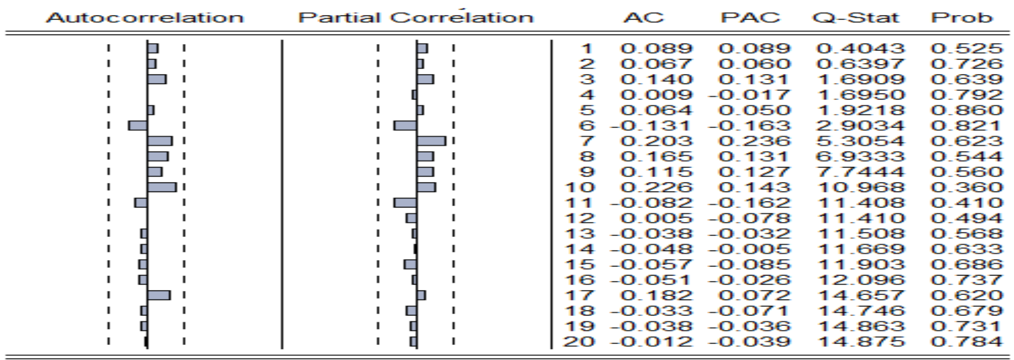


Fig. 5: Actual series, fitted series and residual series of the DL life expectancy at birth (years) sequence

After fitting the ARIMA (1, 1, 1) model, the residual is tested for white noise. Figure 8 shows the autocorrelation and partial autocorrelation function graphs for the residual series. The residual is white noise, which indicates that the model is valid.



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.089	0.089	0.4043	0.525
		2	0.067	0.060	0.6397	0.726
		3	0.140	0.131	1.6909	0.639
		4	0.009	-0.017	1.6950	0.792
		5	0.064	0.050	1.9218	0.860
		6	-0.131	-0.163	2.9034	0.821
		7	0.203	0.236	5.3054	0.623
		8	0.165	0.131	6.9333	0.544
		9	0.115	0.127	7.7444	0.560
		10	0.226	0.143	10.968	0.360
		11	-0.082	-0.162	11.408	0.410
		12	0.005	-0.078	11.410	0.494
		13	-0.038	-0.032	11.508	0.568
		14	-0.048	-0.005	11.669	0.633
		15	-0.057	-0.085	11.903	0.686
		16	-0.051	-0.026	12.096	0.737
		17	0.182	0.072	14.657	0.620
		18	-0.033	-0.071	14.746	0.679
		19	-0.038	-0.036	14.863	0.731
		20	-0.012	-0.039	14.875	0.784

Fig. 6 The residual series' autocorrelation and partial autocorrelation function plots.

For diagnostic checks, the Jarque-Bera Test and The ARCH test of heteroskedasticity. conclude that the residuals follow normal distribution and there is no heteroskedasticity in the residuals., as indicated by a p-value of 0.67, and 0.89, respectively, Multicollinearity was assessed using the variance inflation coefficient, and all values less than 10 indicated that there was no Multicollinearity as shown in table 5.

D-Modeling and Forecasting of the Mortality for Children under Five Years

Table 6 shows the significant parameters ($p<0.01$) for the ARIMA (1,1,1) model.

Table 7: Estimation results of the ARIMA model of the mortality rate for children under five years

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-5.66	2.59	-2.19	0.03
AR (1)	0.96	0.06	14.79	0.00
MA (1)	0.31	0.14	2.26	0.03
SIGMASQ	0.62	0.12	5.14	0.00
R-squared	0.93	Mean dependent var		-5.96
Adjusted R-squared	0.93	S.D. dependent var		3.05

S.E. of regression	0.82	Akaike info criterion (AIC)		2.59
Sum squared resid	29.66	Schwarz criterion (BIC)		2.75
Log likelihood	-58.14	Hannan-Quinn criter.		2.65
F-statistic	200.89	Durbin-Watson stat		1.81
Prob(F-statistic)	0.00			
Inverted AR Roots	0.96			
Inverted MA Roots	-0.31			

The fitted ARIMA (1,1,1) model can be written as: **ΔL the mortality rate for children under five years =-5.66−0.96$y_{t-1} + 0.31e_{t-1} + e_t$ (4)**

The model coefficients' t statistic and P value indicate significant parameter estimates for all explanatory variables at a level of 0.01 and the Constant coefficient (c) of -5.66 this could indicate a long-term trend of declining on the mortality rate for children under five years. The Estimated parameters of the ARIMA model was done using like Maximum Likelihood Estimation (MLE) methods. SIGMASQ The coefficient is 0.62 with a p-value of 0.00. suggesting a good fit between the model and the data. The mean value of -5.96 indicates that the death rate for children under five years averaged -5.96 for the data period. This negative statistic may seem unexpected for a mortality rate, which is normally positive. However, this could be due to how the data is processed or differentiated in the ARIMA model to attain stationarity.

The overall model is statistically significant, as demonstrated by the F-statistic value of 200.89 and the p-value of 0.00. The AR (1) term is significant, indicating that past values of the mortality rate for children under five years effect current values, and the MA (1) term is also significant, implying that earlier errors affect current values. That’s with Inverted AR Roots and Inverted MA Roots of 0.96 and -0.31 respectively indicating that there is stability in the autoregressive process and in the moving average process. And the R-squared is 0.93, indicating the model's robustness. And with low values of All three criteria (AIC, BIC, Hannan-Quinn criteria) which indicates that this model is the best. The model's standard error of regression is 0.82 and Sum Squared Residuals is 29.66, The log likelihood is -58.14, all indicate the model's goodness of fitness. As the best one among the evaluated models, ARIMA (1,1,1) was tested in autocorrelation and heteroscedasticity. Durbin-Watson D statistic was found to be 1.81, very close to 2.00, which means that there is no autocorrelation problem.

To test the heteroscedasticity case of the ARIMA (1,1,1), was found the most suitable model for the time series transformed logarithmically. The obtained new model's coefficients were significant with p- value <0.05. Figure 9 shows the results of fitting the model to the mortality rate for children under five years data. The solid line represents the actual data, while the upper and lower dotted lines represent the model's fitted values and residuals, respectively.

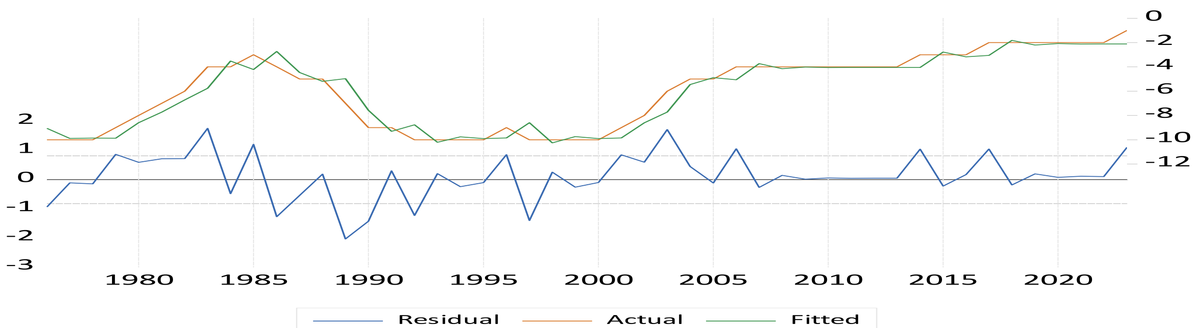


Fig. 7: Actual series, fitted series and residual series of the mortality rate for children under five years sequence

After fitting the ARIMA (1, 1, 1) model, the residual is tested for white noise. Figure 10 shows the autocorrelation and partial autocorrelation function graphs for the residual series. The residual is white noise, which indicates that the model is valid.

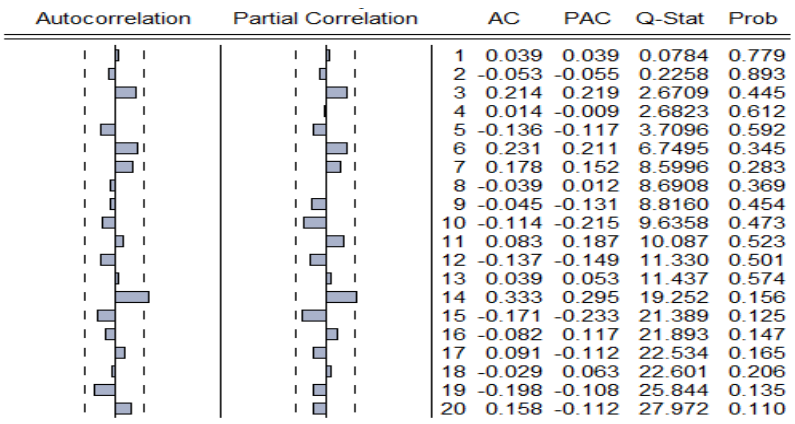


Fig. 8: The residual series' autocorrelation and partial autocorrelation function plots

The ARIMA (1,1,1) model was used for forecasting the mortality rate for children under five years between 2024 and 2030, utilizing a dynamic forecast mode with results listed in Table 7. The results revealed an excellent fit between the actual and fitted values, indicating an important effect on future life expectancy at birth.

Table 8: the mortality rate for children under five years forecasts for the period 2024-2030

Year	2024	2025	2026	2027	2028	2029	2030
forecasted	18.7	20.0	21.8	24.0	26.4	28.8	31.2

Table.7 shows that the forecasts indicated that the mortality rate for children under five years would raise from 18.7 to 31.2. The updated the mortality rate for children under five years for 2024 has not been published by the World Development Indicators.

For diagnostic tests, the Jarque-Bera Test and The ARCH test of heteroskedasticity. conclude that the residuals follow normal distribution and there is no heteroskedasticity in the residuals, as indicated by a p-value of 0.42, and 0. 0.79, respectively.

The next step is to estimate of The Effect of Independent Variables on the mortality rate for children under five years model**.** Table 8 shows the correlation matrix between independent variables and the mortality rate for children under five years.

Table 9: Correlation matrix between independent variables and the mortality rate for children under five years

Variables	Mortality rate for children under five years	Annual freshwater withdrawals	Water productivity	Level of water stress	Population
Mortality rate for children under five years	1				
Annual freshwater withdrawals	-0.828	1			
Water productivity	-0.738	0.798	1		
Level of water stress	0.788	0.727	0.725	1	
Population	0.825	0.841	0.764	0.803	1

As demonstrated in the correlation matrix, there is no correlation above 0.85 between independent variables for all variables included in the analysis.

Table 10 shows the estimation of The Effect of independent variables on the mortality rate for children under five years

Table 11: Estimation of The Effect of independent variables on the mortality rate for children under five years

Variable and parameters	Coefficient	Std. Error	t-Statistic	Prob.	VIF
C	-4.50	3.32	-1.36	0.18	
Annual freshwater withdrawals	-0.01	0.01	-2.59	0.01	1.4
Water productivity	-0.87	0.12	-7.36	0.00	6.0
Level of water stress	0.74	0.14	5.27	0.00	3.2
Population	0.57	0.12	4.60	0.00	2.5
AR (1)	0.99	0.05	18.81	0.00	2.0
MA (1)	0.42	0.20	2.13	0.04	2.1
SIGMASQ	0.14	0.03	4.68	0.00	2.2
R-squared	0.98	Mean dependent var		-5.95	
Adjusted R-squared	0.98	S.D. dependent var		3.0	
S.E. of regression	0.42	Akaike info criterion (AIC)		1.3	
Sum squared resid	6.57	Schwarz criterion (BIC)		1.7	
Log likelihood	-22.85	Hannan-Quinn criter.		1.5	
F-statistic	326.69	Durbin-Watson stat		1.8	
Prob(F-statistic)	0.00				
Inverted AR Roots	0.99				
Inverted MA Roots	-0.42				

The full model can be expressed as follows:

ΔL The mortality rate for children under five years =-0.01* Annual freshwater withdrawals - 0.87* water productivity+ 0.74* water level of water stress +0.57* population + $0.99y_{t-1} + 0.42e_{t-1} + e_t$ (3)

The model coefficients' t statistic and P value indicate significant parameter and coefficients estimates for all explanatory variables at a level of 0.01. The Estimated parameters of the ARIMA model was done using like Maximum Likelihood Estimation (MLE) methods. SIGMASQ (Variance of the Error Term) coefficient is 0.14 with a standard error of 0.001. It ensures that the residuals behave appropriately and that the model does not overfit the data.

The overall model is statistically significant, as demonstrated by the F-statistic value of 326.69 and the p-value of 0.00. The AR (1) term is significant, indicating that past values of life expectancy effect current values, and the MA (1) term is also significant, implying that earlier errors affect current values That's with Inverted AR Roots and Inverted MA Roots of 0.99 and -0.42 respectively indicating that there is stability in the autoregressive process and in the moving average process. And The high R-squared and adjusted R-squared values (both 0.98) indicates that the model explains a large proportion of the variation in life expectancy at birth. And with low values of All three criteria (AIC, BIC, Hannan-Quinn criteria) which indicates that this model is the best. The model's standard error of regression is 0.42 and Sum Squared Residuals of 6.57, which is the total deviation of the observed values from the fitted values. with the log likelihood is -22.85, which indicate the model's goodness of fitness. As the best one among the evaluated models, ARIMA (1,1,1) was tested in autocorrelation and heteroscedasticity. Durbin-Watson D statistic was found to be 1.8, very close to 2.000, which means that there is no autocorrelation problem.

The coefficient of the constant is not significant. The Annual freshwater withdrawals coefficient is -0.01, indicates that each in annual freshwater withdrawals by 100% leads to a decrease in the mortality rate for children under five years by .01%. Water productivity is coefficient of -0.87, indicates that each increase in water productivity by 100% leads to a decrease in the mortality rate for children under five years 87%. Water stress level coefficient is.74, indicates that each increase in water stress levels by 100% leads to an increase in the mortality rate for children under five years by 74%. Population coefficient is 0.57, indicates that each increase in population by 100% leads to an increase in the mortality rate for children under five years by 57%.

To test the heteroscedasticity case of the ARIMA (1,1,1), was found to be the most suitable model for the time series transformed logarithmically. The obtained new model's coefficients were significant with p- value <0.01 Figure 11 shows the results of fitting the model to the Estimated Model. The solid line represents the actual data, while the upper and lower dotted lines represent the model's fitted values and residuals, respectively.

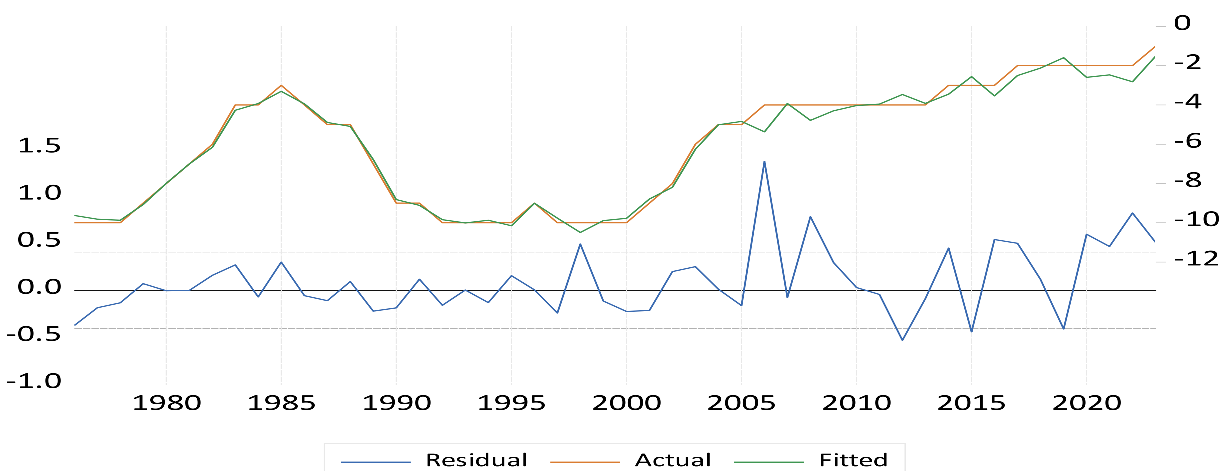
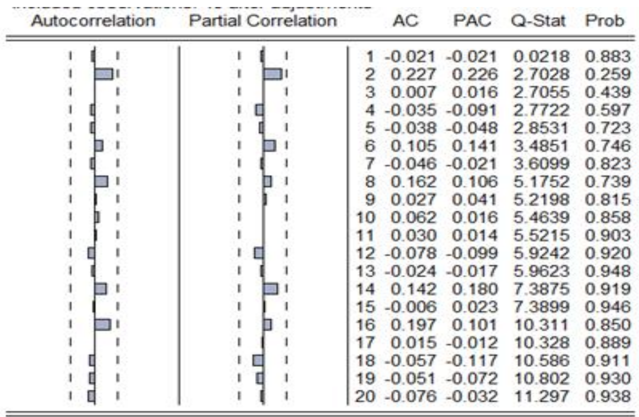


Fig. 9: Actual series, fitted series and residual series of the DL the mortality rate for children under five years sequence

After fitting the ARIMA (1, 1, 1) model, the residual is tested for white noise. Figure 12 shows the autocorrelation and partial autocorrelation function graphs for the residual series. The



	Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
1			-0.021	-0.021	0.0218	0.883
2			0.227	0.226	2.7028	0.259
3			0.007	0.016	2.7055	0.439
4			-0.035	-0.091	2.7722	0.597
5			-0.038	-0.048	2.8531	0.723
6			0.105	0.141	3.4851	0.746
7			-0.046	-0.021	3.6099	0.823
8			0.162	0.106	5.1752	0.739
9			0.027	0.041	5.2198	0.815
10			0.062	0.016	5.4639	0.858
11			0.030	0.014	5.5215	0.903
12			-0.078	-0.099	5.9242	0.920
13			-0.024	-0.017	5.9623	0.948
14			0.142	0.180	7.3875	0.919
15			-0.006	0.023	7.3899	0.946
16			0.197	0.101	10.311	0.850
17			0.015	-0.012	10.328	0.889
18			-0.057	-0.117	10.586	0.911
19			-0.051	-0.072	10.802	0.930
20			-0.076	-0.032	11.297	0.938

Fig. 10: The residual series' autocorrelation and partial autocorrelation function plots.

To diagnostic checks, the Jarque-Bera Test and The ARCH test of heteroskedasticity conclude that the residuals follow normal distribution and there is no heteroskedasticity in the residuals., as indicated by a p-value of 0.37, and 0.68, respectively, Multicollinearity was assessed using the variance inflation coefficient, and all values less than 10 indicated that there was no autocorrelation as shown in table 9.

The above results are consistent to somewhat with the results of previous studies that rely on correlation and regression analysis which confirmed the impact of water scarcity on health and well-being (e.g., Masaharu et al., 2011; Zhu et al., 2023).

2- The Second Study:

This study was based on the data collected using questionnaire. The questionnaire developed for this study included three main parts:

A. **Demographic variables:** These variables included: gender (two categories), income (three categories), and the governorate. The researcher used these variables to explain the results.

B. **Water Scarcity:** Water scarcity dimensions were measured based on Rezaei et al (2017) scale, this scale consists of 26 items, answered on a five-point Likert scale. It ranges from (1) totally disagree to (5) completely agree, and measures the three dimensions of water scarcity. Awareness was measured using ten items (items from AWA1 to AWA10). Examples of these items are: water conservation is essential to prevent water scarcity (AWA1), irrigation water conservation is important and necessary (AWA2), and scarcity of irrigation water is prevented crops production (AWA3). Perception was measured using ten items (Items from PER1 to PER10). Examples of these items are: water scarcity is already more severe than the last (PER1), my residential area is faced with water scarcity (PER2), and the water level in the Nile River is lower than the past (PER3). Adoption/ Behavior was measured using (Items from ADO1 to ADO6). Examples of these items are: I try to reduce the amount of water I drink (ADO1), My family tries to reduce the water used in many areas like food preparation (ADO2), and I have to buy bottled and mineral water to deal with water scarcity and changing quality (ADO3).

C. **Health and Wellbeing:** Health and wellbeing were measured based on Brazier (2022) scale. The researcher used a short version of the original scale, where the researcher combined the items of the third dimension (Severity) into the items of the two other dimensions. The version used became consists of 16 items, it measures two dimensions of health and well-being. Difficulty/problems related to physical health and well-being was measured using six items (items from DIF1 to DIF6), these items was answered on a four-point scale, it ranges from 1 to 4, as follows: (1) no difficulty, (2) slight difficulty, (3) some difficulty, (4) a lot of difficulty and unable. Examples of these items are: during the last six months, how difficult was it for you to see (using, for example, glasses or contact lenses if you usually use them) ? (DIF1), and during the last six months, How difficult was it for you to hear (using, for example, hearing aids if you usually use them) ? (DIF2). Frequency/problems related to psychological health and well-being was measured using ten items (items from FRE1 to FRE10), these items was answered on a five-point scale, it ranges from 1 to 5, as follows: (1) none of the time, (2) only occasionally, (3) sometimes, (4) often, (5) most or all the time. Examples of these items are: during the last six months, I felt exhausted (FRE1), during the last six months, I felt lonely (FRE2), and during the last six months, I had trouble concentrating/thinking clearly (FRE3).

The researcher used Cronbach`s Alpha to assess reliability. Instrument or measure reliability means that the instrument consistently reflects the construct or the variable that it is measuring by giving the same score if used over time or across multiple samples. In other words, reliability is about consistency of a measure. Cronbach`s Alpha is the most famous way of assessing reliability by comparing the amount of shared vaiance, or covariance, among the items making up the measure to the amount of overall variance. Cronbach`s Alpha takes values ranging from zero to one. Generally, a Cronbach`s Alpha value of 0.7 or above is considered acceptable. While values above 0.8 indicate good reliability, and values above 0.9 suggest excellent internal consistency (Cho, 2016; Cronbach, 1951). Cronbach`s Alpha for the three dimensions of water scarcity were 0.84, 0.86, and 0.90, respectively. Cronbach`s Alpha for the two dimensions of health and well-being wee .89 and 0.92, respectively.

It is noted that the researcher relied on the cluster arrangement method, not the random arrangement of the questionnaire form items, by grouping the items designated to measure each dimension with each other before moving to those items designated to measure another dimension, and so on until the items designated to measure each variable are finished, then move to the items designated to measure the dimensions of the other variable (Armstrong, 2012: 728-729).

The researcher controlled and measured common method bias. Common Method Bias (CMB) can appear when both the independent and dependent variables is captured by the same response method. The consequences of common method bias can be detrimental to the study` validity. To control CMB, the researcher used some remedies or procedural methods suggested by Podsakoff and Organ (1986). First, the items intended to measure the dependent variable were placed before the items intended to measure the independent variable in the questionnaire so that the respondent would not infer a sequence of answers when reading the items intended to measure the independent variable first. Second, the questionnaire included some reversecoding items that aim to reveal the concentration degree of the respondent when reading and answering the items. Third, there were differences in anchors or answer alternatives related to variables in terms of titles and numbers, as shown when developing the questionnaire. To measure CMB, two techniques or statistical methods suggested by Podsakoff et al. (2003) were used. First, Harman`s one-factor test was conducted on all items. The principal axis factoring extracted five distinct factors with eigenvalues greater than one that accounted for 49.5% of the total variance, with the first factor account for 28.2% of the variance. Thus, no single factor emerged, nor did one factor account for most of the variance. Second, to confirm this result, a confirmatory factor analysis (CFA) was conducted to analyze if the model fit improved when the complexity of the research was increased (Korsgaard and Roberson, 1995; McFarlin and Sweeney, 1992; Podsakoff et al., 2003). CFA was first developed by Jöreskog (1969). The objective of confirmatory factor analysis is to test whether the data fit a hypothesized measurement model developed based on a theory and/or a previous analytic research (Preedy & Watson, 2009). The results indicated that the single-factor model did not fit the data, thus supporting the results obtained from Harman`s one-factor test. Collectively, the results of these two tests demonstrated that common method variance was not significantly present in the data and posed no threat to the interpretation of the results of the study` validation.

The study population consists of all Egyptian citizens residing in Egypt. The study population is unspecific and unknown in terms of number and identity, because it is impossible to establish a framework for the research population. Therefore, researcher used the following equation to calculate the sample size (Charan & Biswas, 2013):

$$N= (Z^2 \text{ x } P [1-P]) / E^2$$

In the above formula, Z is the ratio of the normal change or the standard degree at the permissible error and equal to 1.96 at a confidence level of 95%, which is the most common in social research; P is the sampling ratio that is usually considered 0.05; and E permitted of error which will specific with regard to the pre-test results, albeit its maximum equals 0.05. Accordingly, by substituting in this equation, the minimum sample size is equal to 384 persons. Although it was a non- probabilistic sample, it was the only technique available to the researcher.

After the researcher developed the questionnaire, she collected the questionnaire data using Meta applications, especially Messenger and whatsapp, to reach the largest possible number of respondents, relying on the concept of snowball sample as one of the types of non-probabilistic sampling. The number of returned questionnaires that were valid for statistical analysis reached 407 questionnaires, exceeding the minimum acceptable sample size (384 persons). All of these questionnaires were subjected to statistical analysis.

As for gender, the sample included 38% male and 62% female. As for income, 23% of the sample had a monthly income of less than 5000 EGP, 61% had a monthly income of 5000 EGP to less than 15000 EGP, and 16% had a monthly income of 15000 EGP or more. As for education, 19% of the sample had less than a university education, 66% had a university education, and 17% had a postgraduate degree. As for the governorate, 81% of the sample were residents of Great Cairo and 19% were residents of other governorates.

The researcher developed the structural model of the study variables. Structural Equation Modeling (SEM) is a sophisticated statistical approach that enables researchers to analyze and explore the relationships between observed variables and underlying latent variables. There are many types of SEM such as path analysis, confirmatory factor analysis, and latent variable structural model (it is mainly using the measured latent variables within the path analysis framework). SEM is distinguished from multiple regression analysis in that SEM deals with both observed and latent variables (models error explicitly), while multiple regression analysis deals only with observed variables (does not admit variable error). Also, SEM includes many dependent variables, unlike multiple regression analysis which includes only one dependent variable (Birick & Kelloway, 2019; Tarka, 2017).

The following figure represents the structural model for the effects of water scarcity dimensions on health and well-being dimensions:

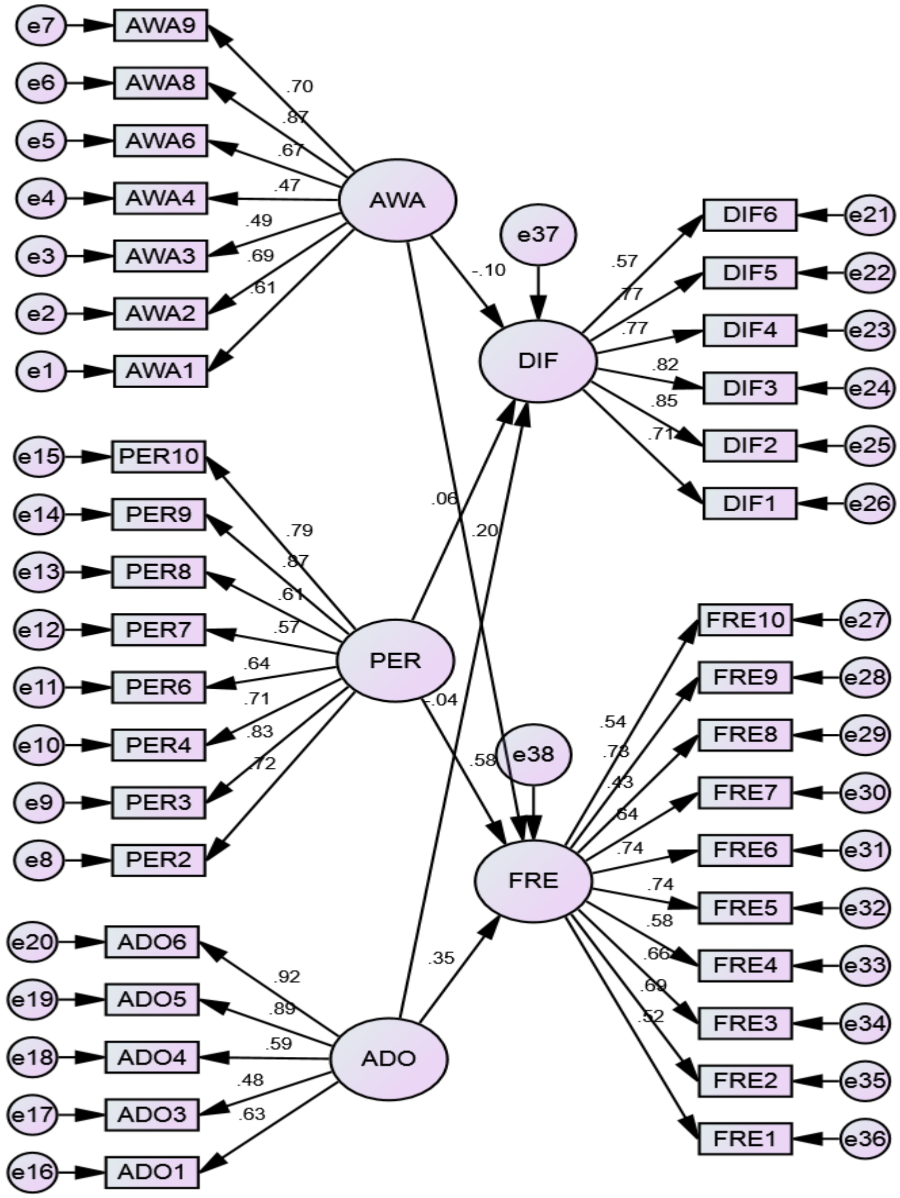


Figure 13: The structural model for the effects of water scarcity dimensions on health and well-being dimensions

To improve the goodness of fit indicators of the structural model, six items were excluded because the factor loading for each item on its dimension was lower than 0.5. The excluded items include three items related to awareness dimension (AWA5, AWA7, and AWA10), two items related to perception dimension (PER1 and PER5), and one item related adoption/ behavior dimension (ADO2). The structure model fits the data well. Normed Chi-square (CMIN/DF) = 4.24 (the standardized value less than or equal to 5). Root Mean Square Error of Approximation (RMSEA) = 0.062 (the standardized value less than 0.08). Goodness of Fit Index (GFI) = 0.954. Comparative Fit Index (CFI) = 0.932. Normed of Fit Index (NFI) = 0.945. Tucker-Lewis Index (TLI) = 0.964. For these last four indicators, the closer the value of each indicator is to one, the better the goodness of fit of the structural model.

The following table represents the results of the structural model:

Table 10: The results of the structural model

The path		Un-standardized Coefficient U.C	Standard Error S.E	Standardized Coefficient S.C	T. Test C.R	P Value
Independent variable	Dependent variable					
AWA	DIF	-.079	.089	-.096	-.895	.371
PER	DIF	.033	.054	.064	.617	.537
ADO	DIF	-.030	.075	-.042	-.407	.684
AWA	FRE	.197	.092	.197	2.145	.032
PER	FRE	.364	.083	.576	4.402	***
ADO	FRE	.309	.092	.353	3.337	***

Note: ***P < 0.01

It is clear from the previous figure and the previous table that difficulty/problems related to physical health and well-being are not statistically affected by any of the three dimensions of water scarcity. This result somewhat contradicts previous studies that based on the questionnaire and surveys which have confirmed the impact of water scarcity on physical health (e.g., Abanyie et al., 2025; Abedin et al., 2019; Shaikh and Birajdar, 2024; Nyemb et al., 2010). This result may due to the fact that most of the sample has medium and high incomes (77%), which enables them to deal with the crisis of water shortage or poor quality of water. Besides, most of the sample has a university degree or postgraduate degree (83%), which enables them to recognize the negative impacts of this crisis on the problems related to physical health and well-being, and thus try to avoid these negative impacts. Also, most of the sample is residents in Great Cairo (81%), where this crisis is less than other governorates, villages, and less civilized places. This result may also be due to that water scarcity crisis has not yet significantly affected the physical health and well-being of citizens.

On the other hand, frequency/problems related to psychological health and well-being are positively and statistically affected by the three dimensions of water scarcity. This result is consistent to somewhat with previous studies that based on the questionnaire and surveys which have confirmed the impact of water scarcity on psychological health (e.g., Rassol et al., 2023; Rhue et al., 2023; Rosing & Young, 2020; Zenko & Menga, 2019). The researcher used the opinions of some philosophers to explain this result. Fyodor Dostoevsky asserted that “I swear that excessive awareness and perception is a disease, a real and dangerous disease. An ordinary awareness is enough for human needs”. Also, Emil Cioran said that “Consciousness is a chronic curse, a terrible disaster. It is our exile. Ignorance is a homeland and Consciousness is an exile”. While Franz Kafka argued that “If there is anything that more dangerous than excessive drugs, then it is undoubtedly excessive awareness and perception of negative things”. In other words, this result reflects that increased awareness and perception of the crisis of water scarcity and accompanying adaptive behavior to this crisis may negatively affect the psychological health and well-being of the person in the form of increased anxiety and tension and a decreased sense of psychological security. The order of the dimensions of water scarcity in terms of the positive impact in frequency is perception, then adoption, and finally awareness. This result seems logical, as awareness may not turn into full perception, and when full perception of negative phenomena occurs, the pressures on the person increase. This positive impact may begin to decrease with the person`s attempt to adapt with the negative phenomena.

Recommendations:

In light of the research results, the researcher recommends the following:

1- Effectively managing water scarcity, it is worth noting that Egypt launched the Water Resources Strategy 2050, which was developed by the Egyptian Ministry of Water Resources and Irrigation in 2020. The strategy focuses on using the principles of integrated water resources management through four axes, which are: developing traditional and non-traditional water resources, rationalizing water use, improving water quality, and creating an appropriate environment for integrated water resources management. In light of the strategy, the researcher proposes the following:

a- Reducing the level of water stress and reducing the amount of water withdrawals from agriculture, as agriculture consumes 75% of water in Egypt. This can be done by reusing agricultural drainage water, modernizing and developing irrigation methods and systems to reduce losses and raise irrigation efficiency, while developing crop varieties that tolerate salinity and drought. It is also preferable to support crops that consume little water, and grow short-lived varieties that mature faster.

b- Improving water productivity, through the need to take into account the economic value of water in the policy and decision-making process, in addition to studying all options available for private sector participation in various water fields with the aim of increasing economic efficiency.

c- Intensifying awareness campaigns on how to rationalize domestic water use.

d- Reducing water withdrawals from industry and public services. This can be done by using rainwater and reusing treated wastewater, known as gray water.

2- Facing the problem of population increase, which the Egyptian government has been trying to address for years, but the matter, still requires more efforts.

3- Paying attention to water quality, in order to reduce water diseases.

4- Providing the necessary health care resulting from lack of water quality.

5- Paying attention to the physical health of citizens, by launching health campaigns such as 100 Million Health, concerned with detecting diseases resulting from water shortages or lack of quality.

6- Supporting the psychological health of citizens, through the presence of government interventions to reassure citizens about the quality of water and its suitability for human use. Sometimes citizens suffer from a type of obsession and anxiety resulting from the occurrence of something related to the Nile or the quality of drinking water, and this is not accompanied by government media intervention that conveys reassurance to citizens.

Research Limitations and Opportunities for Future Research:

1- Objective and methodological limitations:

In the first study, the effect of three indicators of water scarcity, which are annual freshwater withdrawals, water productivity, and level of water stress were measured, in addition to population as a controlled variable (hence the four indicators represent independent variables) on two indicators of health and well-being, which are life expectancy at birth, and mortality rate-under 5, using the ARIMA model. Therefore, the researcher recommends re-researching using other indicators of water scarcity, such as the Falkenmark indicator, water poverty index, and other indicators of health and well-being, and using another technique such as multiple regression analysis.

In the second study, the impact of water scarcity was measured using the Rezaei et al (2017) scale, which used three dimensions in measuring water scarcity: awareness, perception, and adoption on health and well-being using the Brazier (2022) scale, which used two dimensions in measuring health and well-being, namely difficulty (problems related to physical health), and frequency (problems related to psychological health and well-being), using the structural equation modeling. Therefore, the researcher recommends re-researching using another scale that measures water scarcity, and another scale that measures health and well-being, and using another technique such as multiple regression analysis.

2- Place limitations:

The first and the second study were applied to Egypt, so the researcher suggests conducting a comparative analysis on the impact of water scarcity on health and well-being between Egypt and other countries, whether using time series analysis or using questionnaire.

3- Time limitations:

The first study was limited to conducting a time series analysis of the impact of three indicators of water scarcity (annual freshwater withdrawals, water productivity, and level of water stress), in addition to population as a controlled variable, on two indicators of health and well-being (life expectancy at birth and morality rate- under five) using 49 observations from 1975 to 2023 to study the effect of the water scarcity on health and well-being, due to the lack of data on other indicators of health and well-being. Therefore, the researcher recommends repeating the study on other indicators of health and well-being when the time series data are complete.

The second study used the questionnaire, where the data collected electronically using Google form during the period from August to November 2024. Therefore, the researcher recommends re-collecting the questionnaire data at a later time period to monitor the change in the two variables.

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المستخلص

هدف البحث إلى دراسة تأثير ندرة المياه على الصحة والرفاهية في مصر باستخدام دراستين كميتين. في الدراسة الأولى، تم استخدام نموذج ARIMA لنمذجة والتنبؤ بمؤشرين للصحة والرفاهية من خلال فحص تأثير عمليات السحب السنوية للمياه العذبة وإنتاجية المياه ومستوى الإجهاد المائي كثلاثة مؤشرات لندرة المياه، إلى جانب السكان كمتغير مُتحكم فيه. أشارت النتائج إلى أن متوسط العمر المتوقع عند الولادة يتأثر طردياً بعمليات السحب السنوية للمياه العذبة وإنتاجية المياه، بينما يتأثر عكسيًا بمستوى الإجهاد المائي والسكان. في المقابل، كانت نتائج معدل الوفيات - أقل من خمس سنوات متناقضة تمامًا. في ضوء ذلك، تم التنبؤ بمؤشري الصحة والرفاهية في مصر حتى عام 2030. في الدراسة الثانية، تم جمع الاستبيانات من عينة غير احتمالية من 407 فرداً. أشارت النتائج إلى أن الصعوبة (مشاكل الصحة الجسدية) لا تتأثر إحصائياً بأي من أبعاد ندرة المياه الثلاثة، وهي الوعي والإدراك والتكيف/السلوك، بينما يتأثر التكرار (مشاكل الصحة النفسية) تأثيراً طردياً دال إحصائياً بالأبعاد الثلاثة لندرة المياه. *ومن ثم، خرج البحث بمجموعة من* التوصيات التي تساعد في معالجة ندرة المياه في مصر بالإضافة إلى دعم صحة ورفاهية المواطن المصري. ويُعد البحث محاولة لإثراء الدراسات التي تناولت العلاقة بين المتغيرين من حيث أنه جمع بين دراستين كميتين. كما اقترح البحث مجموعة من فرص البحث المستقبلية عند مناقشة حدود البحث.

الكلمات المفتاحية: ندرة المياه؛ الصحة والرفاهية؛ تحليل كمي؛ مصر.