CHAPTER III
RESEARCH METHODS

The main objective of this study is to examines the relationship between financial stability, financial literacy, inclusion, climate change and economic growth in Sub-Saharan Africa countries. The study examines the moderating effects of FinTech on financial literacy and financial inclusion. It also aims to assess the moderating effects of financial stability and FinTech on climate change and financial inclusion, as well as the moderating effects of economic growth and financial stability on FinTech adoption and climate change. Additionally, the study investigates the moderating effect of regulatory quality and financial development on the correlation between financial stability and economic growth. This chapter focuses on the research methods used to achieve this aim, including research design, participants, population and sample, research instruments and data sources, research procedures, and data analysis.

3.1 Research Design

Research in the field of finance has shown that financial literacy, financial inclusion, climate change, and economic growth are crucial factors that impact financial stability in SSA countries (Kouladoum et al., 2022; Tsuchiya, 2023). To better comprehend the relationship between these variables, this study will adopt a quantitative research approach with an explanatory (causal) research design. In an explanatory (causal) research design, researchers aim to determine the cause-and-effect relationships between variables (Sileyew, 2019). This research design is particularly useful in identifying the factors that influence a particular phenomenon and helps to explain why certain events or behaviours occur (Adams & McGuire, 2022). Explanatory (causal) research design typically involves the manipulation of an independent variable, and the observation of the corresponding changes in the dependent variable (Adams & McGuire, 2022). This allows researchers to infer causality, as they can determine if changes in the independent variable lead to changes in the dependent variable (Vebrianto et al., 2020).

An explanatory (causal) research design is particularly suitable for the current study on the combined moderating effects of financial stability and FinTech on climate change and financial inclusion, and the moderating effects of economic growth and financial stability on FinTech adoption and climate change. Additionally, the moderating effect of regulatory quality and financial development on the relationship between financial stability and economic growth. This is because the study aims to determine the causal relationship between the independent variables, moderating variables and the dependent variables in SSA Countries.

3.2 Participants

Participants refer to the individuals, groups, or entities that are included in a research study (Lê & Schmid, 2022). They are the subjects of the study and are often selected based on specific criteria or characteristics that are relevant to the research question (Schwarzkopf, 2024). Participants may provide data through various methods, such as surveys, interviews, or observations, and their responses are used to analyse and draw conclusions about the research topic (Siedlecki, 2020). It is important to ensure that participants are fully informed about the nature of the study and their role in it and that their rights and privacy are respected throughout the research process. The participants in this study are the 48 SSA countries, including Angola, Burkina Faso, Cameroon, the Democratic Republic of Congo, Ethiopia, Ghana, Kenya, Nigeria, South Africa, Tanzania, and Uganda, among others (World Bank Group, 2022).

The selection of the participants in this study is based on the availability of relevant data on financial literacy, financial inclusion, climate change, economic growth, financial stability, financial development, regulatory quality and Fintech adoption and their components. Data was collected from secondary sources such as the World Bank, the International Monetary Fund (IMF) Financial Capability Surveys and the Global Financial Inclusion (Global Findex) Database. The specific characteristics of the participants include their economic, social, and political status, which are crucial factors in understanding the relationship between financial literacy, financial inclusion, climate change, economic growth, financial stability, financial development, regulatory quality, and Fintech adoption in the SSA region. The selection of SSA countries is based on their financial inclusion status, vulnerability to climate change impacts, and overall economic status (World Bank Group, 2022).

According to the World Bank Group (2022), SSA has been identified as one of the most financially excluded regions in the world, with limited access to financial services, high poverty rates, and vulnerability to climate change impacts. The region has also been identified as having significant potential for FinTech adoption due to the growing demand for digital financial services and increasing mobile phone penetration rates (International Monetary Fund, 2018; Yeyouomo et al., 2023). Therefore, the selection of SSA countries as participants in this study is appropriate, as it allows for a comprehensive analysis of the relationship between financial literacy, financial inclusion, climate change, economic growth, financial stability, financial development, regulatory requirement, and FinTech adoption in a region that is facing significant challenges in these areas (Yeyouomo et al., 2023). The inclusion of multiple SSA countries in the study will also provide a diverse and representative sample, enhancing the generalizability of the study findings.

3.3 Population and Sample

Population refers to the entire group of individuals, objects, or events that share common characteristics and are of interest to the researcher. In this study, the population is SSA countries which consist of 48 countries as reported by the World Bank in 2022 (World Bank Group, 2022). A sample frame, on the other hand, is a list of all the individuals, objects, or events in the population from which a sample is drawn. The sample frame includes all SSA countries except for Comoros due to the insufficient relevant data to cover the period of 2005- 2022. Therefore, the sample size for this study is 47 SSA countries.

To determine the sample, quantitative procedures and data availability were considered. Data were collected from reliable secondary sources as stated earlier. These sources provide a comprehensive set of data on financial literacy, financial inclusion, climate change, economic growth, financial stability, financial development, regulatory quality, and Fintech adoption in the SSA region. The sample was selected using a stratified random sampling technique. The SSA countries were divided into four strata based on their regional classification as reported by the World Bank. The four strata are West Africa, Central Africa, Eastern Africa, and Southern Africa. A proportional sampling technique was used to randomly select countries from each stratum based on their contribution to the total population of the stratum. The countries sampled for this study were selected based on their availability of relevant data and their representation of the different income levels in the SSA region.

The selected countries for this study are Angola, Benin, Botswana, Burkina Faso, Burundi, Cameroon, Central African Republic, Chad, Congo, Democratic Republic of Congo, Republic of Côte d'Ivoire, Djibouti, Equatorial Guinea, Eritrea, Eswatini, Ethiopia, Gabon, Gambia, Ghana, Guinea, Guinea-Bissau, Kenya, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritania, Mauritius, Mozambique, Namibia, Niger, Nigeria, Rwanda, Senegal, Seychelles, Sierra Leone, Somalia, South Africa, South Sudan, Tanzania, Togo, Uganda, Zambia, and Zimbabwe. These countries represent the different income levels in the SSA region, and their selection is justified by their availability of relevant data (see regional classification of SSA countries in appendix 1).

3.4 Research Instrument and Data Sources

The instruments and data collection tools used in the research are secondary sources of data. The World Bank, the International Monetary Fund (IMF) and Financial Capability Surveys and Global Financial Inclusion (Global Findex) data on financial literacy, financial inclusion, climate change, economic growth, financial stability, financial development, regulatory requirement, and Fintech adoption in the SSA region are primarily collected through a variety of quantitative methods. The methodology used to collect the data is based on standardized surveys, censuses, administrative records, and other primary and secondary sources (World Bank Group, 2022). For financial literacy and financial inclusion, the World Bank and IMF collect data through a range of household surveys, such as the Global Findex database. The Global Findex survey is a demand-side survey of individuals' use of financial services and their views on financial matters, which has been conducted in over 140 countries. The survey collects data on individuals' access to and use of financial services, including accounts, credit, payments, and insurance. The survey also includes questions on financial literacy and consumer protection (Demirgüç-Kunt et al., 2022; World Bank Group, 2022).

For Fintech adoption, the World Bank and IMF collect data through a range of primary and secondary sources, such as surveys of Fintech companies and their customers, as well as data on Fintech investment and regulation. The data collected includes information on the use of digital financial services, such as mobile money and online banking, and the adoption of new financial technologies, such as blockchain and artificial intelligence.

Regarding climate change, the World Bank and IMF collect data through a range of primary and secondary sources, such as climate models, satellite imagery, and weather stations. The data collected includes information on temperature, precipitation, sea level, and greenhouse gas emissions (International Monetary Fund, 2018; World Bank, 2021). In terms of economic growth, the World Bank and IMF collect data through a range of primary and secondary sources, such as national accounts, the balance of payments statistics, and surveys. The data collected includes information on real GDP growth rate, trade openness, financial development index, regulatory quality, and income levels, education attainment. For financial stability, the World Bank and IMF collect data through a range of primary and secondary sources, such as supervisory data from central banks, stock market data, and credit ratings (World Bank, 2021). The data collected includes information on financial sector performance, such as the health of banks and other financial institutions, as well as systemic risk factors (World Bank Group, 2022).

Validity and reliability are important considerations when using secondary sources of data. The World Bank and IMF are known for their rigorous data collection and validation processes, which ensure the accuracy and reliability of the data they provide. The data is collected from various sources, including national statistical agencies, international organizations, and academic institutions. The World Bank and IMF use standardized data collection methods and tools to ensure consistency and comparability of data across countries and regions (World Bank, 2021). The technical use of the data involves cleaning, processing, and analysing the data to produce meaningful results. The data is cleaned to remove any errors or inconsistencies, and missing data are imputed using appropriate methods. The data is then processed using statistical software, such as STATA and SPSS to generate descriptive statistics and conduct regression analysis. To ensure the validity and reliability of the analysis, the data is subjected to various checks and tests. These tests include data cleaning, which involves identifying and correcting errors and inconsistencies in the data, and data normalization, which is the process of adjusting the data to a common scale to facilitate comparison between variables.

3.5 Research Procedures

Research procedure refers to the step-by-step process followed in researching to ensure that the study is well-designed, conducted systematically, and produces reliable and valid results (Kumar, 2019). It involves a systematic approach to gathering, analysing, and interpreting data in a manner that is consistent with the research objectives and questions (Basias & Pollalis, 2018). The research procedure helps to ensure that the research is conducted in an organized and efficient manner and that the results obtained are accurate and reliable (Siedlecki, 2020).

The research problem is the first step in conducting any research, and in this study, the research problem is to investigate the relationship between financial literacy and financial inclusion, climate change and financial inclusion, financial stability and climate change, FinTech adoption and climate change, and economic growth and financial stability in Sub-Saharan Africa countries. This study further examines the moderating effect of Fintech adoption on the relationship between financial literacy and financial inclusion, the moderating role of Fintech adoption and financial stability on the relationship between financial inclusion and climate change, the moderating effect of economic growth on the association between climate change and financial stability, the moderating influence of financial stability on the link between Fintech adoption and climate change, and the joint moderating effects of financial development and regulatory quality on the relationship between economic growth and financial stability.

The research questions and hypotheses were then developed based on the research problem. The research questions are in the form of direct and moderating relationships: The direct relationship questions are as follows: **(1a)** what is the relationship between financial literacy and financial inclusion, **(2a)** what is the relationship climate change and financial inclusion, **(3a)** what is the association between financial stability and climate change, **(4a)** what is the relationship between FinTech adoption and climate change, and **(5a)** what is the relationship between economic growth and financial stability in Sub-Saharan Africa countries. The moderating relationship questions are as follows: (**1b)** what is the moderating effect of FinTech adoption on the relationship between financial literacy and financial inclusion in SSA countries? **(2b)** what is the moderating role of FinTech adoption and financial stability on the relationship between financial inclusion and climate change in SSA countries? **(3b)** what is the moderating effect of economic growth on the association between climate change and financial Stability in SSA countries? **(4b)** what is the moderating influence of financial stability on the link between FinTech adoption and climate change in SSA countries? **(5b)** How do financial development and regulatory quality jointly moderate the relationship between economic growth and financial stability in SSA countries?

Based on the research questions, the following hypotheses were developed for direct and moderating relationships as follows: The direct relationship hypotheses are as follows: **H1a**: Financial literacy has a significant positive relationship with financial inclusion in SSA countries. **H2a**: Financial inclusion has a significant and positive nexus with climate change in SSA countries, H**3a**: There exist a significant negative effect association between climate change and financial stability in SSA countries and **H4a**: FinTech adoption has a significant positive influence on climate change in SSA countries and **H5a:** Economic growth has a significant and positive relationship with financial stability in SSA countries. The moderating hypotheses are as follows: **H1b**: FinTech adoption moderates the relationship between financial literacy and financial inclusion in SSA countries. **H2b:** FinTech adoption moderates the positive relationship between financial inclusion and climate change in SSA countries and **H2c:** Financial stability positively moderates the relationship between financial inclusion and climate change in SSA countries. **H3b**: Economic growth moderates negative association between climate change and financial stability in SSA counties. **H4b**: Financial stability moderates the positive relationship between FinTech adoption and climate change in SSA countries. **H5b**: Financial development positively moderates the relationship between economic growth and financial stability in SSA countries and **H5c**: Regulatory quality positively moderates the relationship between economic growth and financial stability in SSA countries

A literature review was conducted to provide a comprehensive understanding of the existing literature related to the research problem and help develop the theoretical framework for the study. The literature review for this study focuses on financial literacy and financial inclusion, climate change and its impact on economic growth and financial stability, and fintech adoption and its impact on financial inclusion, economic growth, financial development, regulatory requirements, and financial stability.

The research design is a quantitative research design that involves collecting and analysing numerical data. The sample consists of SSA countries (47), selected based on their availability of relevant data and their representation of the different income levels in the SSA region. Data was collected from secondary sources and analysed using statistical software such as Microsoft Excel, STATA version 15.1 and SPSS version 26. The data analysis involves descriptive statistics, correlation analysis, regression analysis, and moderation analysis. The study employs both static and dynamic panel models. The study employed a two-step dynamic model GMM as our baseline model to address endogeneity concerns. To ensure the robustness of the findings, the study conducted sensitivity analyses and robustness testing using alternative models. This included a random effects model under the static assumption and a quantile regression model to account for potential heterogeneity in the data from SSA. Finally, the results of the data analysis were interpreted, and the implications of the findings were identified. Recommendations for policy and practice were provided based on the research findings.

3.5.1 Measurement of variables

3.5.1.1 Financial stability

Financial stability refers to the ability of a financial system to operate effectively and efficiently, withstand external shocks, and avoid causing disruptions to the broader economy (Aikman et al., 2019). Measuring financial stability is crucial in identifying potential risks and vulnerabilities in the financial system and taking appropriate policy measures to prevent or mitigate them (Edge & Liang, 2019). There are several variables used to measure financial stability, including the interest rate spread, bank concentration, non-performing loans to gross loans, bank capital to total assets, credit-to-GDP ratio, and government debt-to-GDP ratio. These variables provide a comprehensive picture of the financial system's overall stability and its ability to withstand shocks (Ma, 2020).

To compute the Financial Stability Index, a statistical approach such as principal component analysis (PCA) can be used. The PCA approach involves constructing an index by combining individual variables, which are assigned weights based on their relative importance in contributing to financial stability (Apea-Bah et al., 2015; Wendong et al., 2024). PCA reduces the dimensionality of the variables, taking into account the correlations between them, and provides a more reliable measurement of financial stability (Kamari & Schultz, 2022).

The formula for computing the Financial Stability Index using PCA is as follows:

$$FinSI = \sum (wi \times xi) \tag{3.1}$$

where:

$FinSI$ = Financial Stability Index

wi = Weights assigned to each variable

xi = Values of each variable

By using the above formula, the Financial Stability Index was calculated, and a higher value of the index indicates greater financial stability. The index was used to track changes in financial stability over time and to identify potential risks and vulnerabilities in the financial system.

3.5.1.1.2 Financial literacy

Financial literacy refers to the ability of individuals to understand and manage their finances effectively. It is an important aspect of personal finance and is essential for making informed financial decisions. The measurement of financial literacy can help to identify gaps in knowledge and inform policies and programs aimed at improving financial literacy (Yan et al., 2021). One common measure of financial literacy is the proportion of the adult population who can answer a set of financial literacy questions correctly. The questions typically cover topics such as budgeting, saving, debt management, and investments (Van Nguyen et al., 2022a).

For example, a common set of questions used to measure financial literacy is the Big Three questions, which are:

1. Suppose you have $100 in a savings account and the interest rate is 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow? a) More than $102 b) Exactly $102 c) Less than $102
2. Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After one year, would the money in the account buy more than it does today, the same as it does today or less than it does today? a) More b) the same c) Less
3. Please tell me whether this statement is true or false: "Buying a single company's stock usually provides a safer return than a stock mutual fund." a) True b) False c) Do not know

The proportion of the adult population who can answer three out of these seven questions correctly is often used as a measure of financial literacy. This measure is useful because it is easy to administer and provides a simple threshold for determining whether individuals have a basic level of financial knowledge (Demirgüç-Kunt et al., 2022). To calculate the proportion of the adult population who can answer three out of the seven financial literacy questions correctly, a survey is typically conducted that includes these questions. The survey results are then analysed to determine the percentage of respondents who answered three or more questions correctly (World Bank, 2021).

3.5.1.1.3 FinTech adoption

FinTech adoption refers to the use of technology-based financial services by individuals and businesses (Allahham et al., 2024; Senyo & Osabutey, 2020). Measuring FinTech adoption is important for understanding the level of technological penetration in the financial sector, tracking trends in consumer behaviour, and informing policymaking and business strategies. To measure FinTech adoption, variables such as mobile money account ownership, digital insurance, and digital payments (Lisha et al., 2023; World Bank, 2021). These variables can be combined to create a composite index that reflects the overall level of FinTech adoption in a given country or region.

One statistical technique for computing the FinTech adoption index is PCA which identifies the underlying structure among a set of variables and produces a smaller number of composite variables that summarize the information contained in the original variables. By applying PCA to standardized data on the selected variables, we will obtain the principal components that represent linear combinations of the original variables.

The weights assigned to each principal component were used to compute the FinTech adoption index using the formula:

$$FinAI = w_1PC_1 + w_2PC_2 + w_3PC_3 \tag{3.2}$$

where $w1$, $w2$ and $w3$ are the weights assigned to each principal component, and PC_1 PC_2 and PC_3 are the values of each principal component. The weights are determined based on the proportion of variance explained by each principal component. Thus, if PC_1 explains 50% of the total variation in the data, PC_2 explains 30%, and PC_3 explains 20%, the study assigns weights of 0.5, 0.3, and 0.2 to each principal component, respectively. By using the FinTech adoption index, changes in FinTech adoption over time can be monitored and compare adoption rates across different countries or regions.

3.5.1.1.4 Financial inclusion

Financial inclusion refers to the provision of affordable and accessible financial services to individuals and businesses, particularly those who are underserved or excluded from the formal financial system (World Bank Group, 2022). The measurement of financial inclusion is important for identifying the level of access to financial services and informing policies and strategies to promote financial inclusion. Several variables can be used to measure financial inclusion, including account usage, transaction volume, account ownership, branch density, credit penetration, and insurance penetration (Ofoeda et al., 2024; World Bank Group, 2022). These variables provide a comprehensive picture of the level of financial inclusion in a country or region and can be used to construct a composite index to measure financial inclusion.

PCA was used to compute the financial inclusion index (*FinII*). To use PCA to compute the financial inclusion index, data collected on the variables of interest: account usage, transaction volume, account ownership, branch density, credit penetration, and insurance penetration will be used. The data was then standardised to ensure that each variable had the same scale. Next, the PCA was used to the standardized data to obtain the principal components. The principal components represent linear combinations of the original variables that capture the maximum amount of variation in the data. The study then uses the weights assigned to each principal component to compute the financial inclusion index.

The formula for computing the financial inclusion index using PCA is as follows:

$$FinII = w_1 PC_1 + w_2 PC_2 + w_3 * PC_3 + w_4 PC_4 + w_5 PC_5 + w_6 PC_6 \tag{3.3}$$

where: w_1, w_2, w_3, w_4, w_5, *and* w_6 are the weights assigned to each principal component PC_1, PC_2, PC_3, PC_4, PC_5, *and* PC_6 are the values of each principal component, which are computed from the standardized data using PCA.

The weights were determined based on the proportion of variance explained by each principal component. For example, if PC_1 explains 50% of the total variation in the data, PC_2 explains 30%, PC_3 explains 10%, PC_4 explains 5%, PC_5 explains 3%, and PC_6 explains 2%, and assign weights of 0.5, 0.3, 0.1, 0.05, 0.03, and 0.02 to each principal component, respectively. By using the above formula, the financial inclusion index can be computed, and a higher value of the index indicates greater financial inclusion. The index can be used to monitor changes in financial inclusion over time and to compare inclusion rates across different countries or regions.

3.5.1.1.5 Climate change

Climate change refers to the long-term changes in global weather patterns, such as rising temperatures, increased frequency of extreme weather events, and changes in precipitation (Raihan et al., 2022). The measurement of climate change is important in understanding the impact of human activities on the environment and identifying potential risks and vulnerabilities (Ahenkan, 2020; Bouraima et al., 2024). Several variables were used to measure climate change, including greenhouse gas emissions, carbon dioxide emissions, methane emissions, nitrous oxide emissions, energy use, and renewable energy consumption. These variables are indicative of the extent to which human activities are contributing to climate change and are used to construct a composite index to measure the severity of climate change (Nuruzzaman et al., 2024; Sadiq et al., 2024).

Principal Component Analysis (PCA) is one way to compute the Climate Change index (CChI). PCA is a statistical technique that identifies the underlying structure among a set of variables and produces a smaller number of composite variables that summarize the information contained in the original variables. To use PCA to compute the Climate Change index, data on the variables of interest such as greenhouse gas emissions, carbon dioxide emissions, methane emissions, nitrous oxide emissions, energy use, and renewable energy consumption are collected. The data was standardized to ensure that each variable had the same scale. The study then applies PCA to the standardized data to obtain the principal components. The principal components represent linear combinations of the original variables that capture the maximum amount of variation in the data. The weights can then be assigned to each principal component to compute the Climate Change index.

The formula for computing the Climate Change index using PCA is as follows:

$$CChI = w_1PC_1 + w_2PC_2 + w_3 * PC_3 + w_4PC_4 + w_5PC_5 + w_6PC_6 \quad (3.4)$$

where: w_1, w_2, w_3, w_4, w_5, *and* w_6 are the weights assigned to each principal component PC_1, PC_2, PC_3, PC_4, PC_5, *and* PC_6 are the values of each principal component, which are computed from the standardized data using PCA.

The weights were determined based on the proportion of variance explained by each principal component. For example, if PC_1 explains 40% of the total variation in the data, PC_2 explains 25%, PC_3 explains 15%, PC_4 explains 10%, PC_5 explains 5%, and PC_6 explains 5%, the assign weights of 0.4, 0.25, 0.15, 0.1, 0.05, and 0.05 to each principal component, respectively. By using the above formula, the Climate Change index was computed, and a higher value of the index indicates greater severity of climate change. The index is used to monitor changes in the severity of climate change over time and to compare severity levels across different countries or regions.

3.5.1.1.6 Economic growth

The measurement of economic growth is typically based on the Real Gross Domestic Product (GDP) growth rate, which is the percentage increase in the value of all goods and services produced by a country's economy over a specific time, adjusted for inflation. The formula for calculating the Real GDP growth rate is:

$$Real\ GDP\ growth\ rate\ =\ \frac{(Real\ GDP\ in\ current\ year\ -\ Real\ GDP\ in\ previous\ year)}{Real\ GDP\ in\ previous\ year} \times 100\%$$

Real GDP refers to the value of all goods and services produced by a country's economy during a specific period, adjusted for inflation. It is calculated by subtracting the value of intermediate goods and services used in the production process from the value of final goods and services produced (Ofoeda et al., 2024; Osamwonyi & Kasimu, 2013). The Real GDP growth rate is an important indicator of a country's economic performance, as it reflects the rate at which its economy is expanding or contracting (Zhou et al., 2022). A higher growth rate indicates that the economy is expanding at a faster pace, while a lower growth rate suggests a slower pace of expansion. The Real GDP growth rate can be used to compare the economic performance of different countries or regions, as well as to track the performance of a country's economy over time. It is also used by policymakers to assess the effectiveness of economic policies and to make decisions about future policy direction (Akinlo & Ounlola, 2021; Chinoda & Kapingura, 2024).

3.5.1.1.7 Control variables

In the methodology section of the study on the selection of control variables, a rigorous approach was adopted to ensure the robustness and relevancy of the variables included in the analysis. The selection was guided by both theoretical and empirical considerations, aiming to account for potential confounding factors while analyzing the relationships among financial literacy, inclusion, and stability within Sub-Saharan Africa. The choice of control variables was critically informed by existing literature and theoretical frameworks that highlight the key factors influencing financial systems in SSA. Variables such as educational attainment, income level, access to technology, changes in income distribution, trade openness, and political stability were included to comprehensively capture the socioeconomic dynamics that could affect the study's primary outcomes. These variables are understood to impact financial literacy and inclusion directly and indirectly, thus controlling for them helps isolate the effects of the main variables of interest (Zhai et al., 2023).

Empirical evidence from similar studies also played a crucial role in shaping the selection. By reviewing prior research that assessed the interplay of financial literacy, stability, and inclusion, the study was able to adopt control variables that have been empirically validated as significant influencers of financial outcomes in the region. This alignment with empirical evidence ensures that the analysis remains grounded in observable reality and enhances the credibility of the findings. Furthermore, the data availability for each selected control variable was verified from reliable secondary sources, ensuring that all variables included in the model could be accurately measured and consistently applied across the various SSA countries studied (World Bank Group, 2022). This careful consideration of data availability helps in maintaining the integrity of the model's estimations and supports the generalizability of the study's conclusions across the region.

Statistical tests were also conducted to ensure that the inclusion of these control variables did not introduce multicollinearity into the model, which could distort the effects of the variables of interest. Each control variable was tested for its unique contribution to the model, ensuring that they provide significant explanatory power without overlapping effects that could cloud the analysis. By systematically selecting control variables based on theoretical relevance, empirical evidence, data availability, and statistical robustness, the study strengthens its methodological foundation. This thorough approach not only enhances the reliability of the results but also provides a clear pathway for replicating and validating the findings in future research.

Changes in income distribution: The measurement of changes in income distribution is important to assess the distribution of wealth in a society. It is typically measured using the Gini coefficient, which ranges from 0 (perfect equality, where everyone has the same income) to 1 (perfect inequality, where one person has all the income and everyone else has none). Other measures of income distribution include the Palma ratio, which compares the income share of the top

10% to the income share of the bottom 40%, and the Atkinson index, which takes into account the degree of aversion to income inequality (Kim, 2016).

Political stability: The measurement of political stability is important to assess the risk of political instability, which can have significant economic and social costs (Sabir & Khan, 2018). It is typically measured using various indicators, such as the number of coups and revolutions, the frequency of protests and riots, and the level of corruption. These indicators can be combined to create a political stability index that provides a comprehensive measure of the overall level of political stability in a country or region (Sabir & Khan, 2018).

Access to technology: The measurement of access to technology is important to assess the level of technological development in a society. It is typically measured using various indicators, such as the number of internet usage (Zhou et al., 2022). These indicators can be combined to create a technology access index that provides a comprehensive measure of the overall level of access to technology in a country or region.

Trade openness: The measurement of trade openness is important to assess the level of integration of a country or region into the global economy. It is typically measured using trade as a percentage of GDP in this study.

Income Levels: The GNIPc measure represents the average revenue generated per person in a country by dividing the total Gross National Income (GNI) by the population (Chang et al., 2019). The amount provided is in current US dollars and does not account for inflation or differences in buying power across countries. GNIPc is a commonly used measure of economic health since it represents the overall size and effectiveness of an economy (International Monetary Fund, 2003). Higher GNIPc scores often indicate better access to resources, higher living standards, and more growth potential (Degbedji et al., 2024).

Education Attainment: Education attainment (EducA) refers to the percentage of adults aged 25 and older who have completed a lower secondary education, which is typically equivalent to nine to ten years of formal instruction (World Bank, 2021). This metric signifies the level of educational attainment among the adult populace, a critical factor in the formation of human capital, progress in the economy, and advancement of society. The frequent utilisation of EducA is due to the significant influence that education experts have on the progress of both individuals and societies (Langley & Leyshon, 2021). Ideals of higher education are associated with Individuals who possess advanced levels of education frequently exhibit higher levels of productivity and contribute more significantly to the economy (Eze et al., 2020). Education has the potential to enhance individuals' health knowledge, behaviours, and accessibility to healthcare. Enhanced social mobility, education has the potential to offer opportunities for families and individuals to progress up the social hierarchy (World Bank, 2023a). Finally, educated citizens are more likely to participate in democratic processes and engage in civic activities (World Bank, 2023a). The measurement of the variables is summarised in Table 3.1.

Table 3.1 Measurement of Financial Stability Index variables

Variable	**Notation**	**Measurement**	**Sources**
Financial Stability Index (FinSI)			
Interest Rate Spread	IRS	Difference between lending and deposit interest rates	IMF, IFS
Bank Concentration	BC	Percentage of total assets held by the largest banks	IMF, IFS, World Bank
Non-Performing Loans to gross loans	NPL	The ratio of non-performing loans to total gross loans	IMF, IFS, World Bank
Bank Capital to Total assets	BCTA	The ratio of bank capital to total assets	IMF, IFS, World Bank
Credit-to-GDP ratio	CGDP	The ratio of credit to the private sector to GDP	IMF, IFS, World Bank
Government debt-to-GDP ratio	GDGDP	The ratio of gross government debt to GDP	IMF, IFS, World Bank

Source: Author (2024)

Table 3.2 Measurement of FinTech, Financial development, Inclusion, Literacy and Regulatory Quality Variables

Variable	**Notation**	**Measurement**	**Sources**
FinTech Adoption Index (FnAI)			
Mobile Money Account Ownership	MMAO	Percentage of adults who report having a mobile money account	World Bank Global Findex
Digital Insurance	DigI	As indicated as a proportion of the overall insurance premiums, the penetration rate of policies acquired and administered via mobile or online platforms.	World Bank Global Findex
Digital Payments	DP	Percentage of adults who report making or receiving digital payments in the past year	World Bank Global Findex
Financial Development Index (FDevI)			
Financial Development Index	FDevI	The composite index of financial system development	International Monetary Fund (IMF)
Regulatory Quality (RQua)			
Regulatory quality	RQ	The composite index of regulatory quality and supervision	World Bank
Financial Literacy (FinL)			
Financial Literacy	FinL	The proportion of the adult population who can answer 3 out of the 7 questions correctly	World Bank, Financial Capability Surveys
Financial Inclusion (FinII)			
Account Usage	AU	Percentage of adults who have an account at a formal financial institution and have used it in the past 12 months for deposit, withdrawal, or any other transaction	World Bank Global Findex
Account Ownership	AO	Percentage of adults who have an account at a formal financial institution	World Bank Global Findex
Branch Density	BD	Number of bank branches per 100,000 adults in a country	World Bank Global Findex

Credit Penetration	CP	Percentage of adults who have borrowed from a formal financial institution in the past year	World Bank Global Findex

Table 3.3 Measurement of Climate Change and Control Variables

Variable	Notation	Measurement	Sources
Climate Change (CChI)			
Greenhouse gas emissions	GHG	Total greenhouse gas emission (kt of CO2 equivalent)	World Bank
Carbon dioxide emissions	CO2	Metric tons per capita	World Bank
Methane emissions	CH4	Kilograms of CO2 equivalent per capita	World Bank
Nitrous oxide emissions	N2O	Kilograms of CO2 equivalent per capita	World Bank
Energy use	ENE	Kilograms of oil equivalent per capita	World Bank
Renewable energy consumption	REN	Percentage of total final energy consumption	World Bank
Economic Growth (GDPGR)			
Real GDP growth rate	GDPGR	The annual percentage growth rate of real GDP	World Bank Data
Control Variables			
Changes in income distribution	Gini	Gini index or poverty headcount ratio	World Bank Data
Political stability	PoS	Worldwide Governance Indicators	World Bank Data
Access to technology	ATech	Internet usage	World Bank Data
Trade openness	TOp	Trade as a percentage of GDP	World Bank Data
Income Levels	GNIPc	Gross national income per capita at current US dollars	World Bank Data
Education Attainment	EducA	Percentage of population aged 25 and older who have completed at least lower secondary school education.	World Bank Data

Source: Author (2024)

3.6 Data Analysis

3.6.1 Dynamic panel models

The importance of utilizing dynamic panel models to analyse the relationship between FinTech adoption, financial literacy, and inclusion, financial development, regulatory quality and financial stability cannot be overemphasized. These models consider the influence of past values on current outcomes, offering a comprehensive understanding of the gradual development of these characteristics over time. The application of this model, promotes assessment of the immediate and long-term impacts of FinTech on financial inclusion, literacy, stability, financial development, and regulatory quality, taking into account past interactions and potential future advancements. The relevance of dynamic panel models is highlighted in research focusing on the effects of economic growth and financial stability on FinTech adoption and climate change. Additionally, the study explores how the combination of financial stability and FinTech influences climate change and financial inclusion. Examining the dynamic dependencies among these factors, dynamic panel models can provide valuable insights into how FinTech shapes financial inclusion, particularly when considering the moderating effects. The study employed the Generalized Method of Moments (GMM).

The Generalized Method of Moments (GMM) is a statistical technique used to estimate the parameters of a model based on moment conditions. It is commonly used in econometrics to estimate the parameters of economic models (Wang et al., 2011). The GMM estimation method is particularly useful when the assumptions required for other estimation techniques, such as the maximum likelihood estimation, are not met (Moral-Benito et al., 2019). The GMM model requires the sample size to be larger than the number of parameters to be estimated (N > T). This condition ensures that there is sufficient information in the data to identify the unknown parameters accurately.

3.6.2.1 Conditions for GMM estimation:

Moment conditions: Moment conditions are a set of equations that relate the parameters of the model to the sample moments of the data. These conditions must be valid and have the same number of equations as the number of parameters being estimated (Han & Phillips, 2006).

Valid instruments: GMM requires that the instruments used to estimate the parameters of the model are valid. Valid instruments are variables that are correlated with endogenous variables but are not correlated with the error term (Kapetanios & Marcellino, 2010).

Over-identification: GMM requires that there are more moment conditions than parameters being estimated. This is known as over-identification and helps to ensure that the estimates are efficient (Wang et al., 2011).

Moment conditions should be independent and exogenous: Moment conditions should be independent and exogenous, which means that they should not be influenced by the error term of the model.

Compared to static models, the GMM model offers several advantages. First, it allows for the estimation of models with endogenous explanatory variables, where the traditional OLS regression would lead to biased and inconsistent results. Second, it can handle measurement errors in the explanatory variables, which would also affect the validity of the OLS estimates. Finally, it provides more efficient estimates than OLS when the model's assumptions are not fully met.

The General GMM model can be expressed as follows:

$$\theta \ = \ argmin \ \left(g\left(\theta\right)'Wg\left(\theta\right)\right) \tag{1}$$

where θ represents the vector of parameters being estimated, $g(\theta)$ is a vector of moment conditions, and W is a weighting matrix. The weighting matrix W is typically chosen to be a positive semi-definite matrix that is based on the variance-covariance matrix of the moment conditions. The GMM model is solved using an iterative procedure, where the initial estimates of the parameters are refined until the moment conditions are satisfied. Once the estimates have been obtained, they can be used to make predictions about the behaviour of the model.

3.6.2.2 Empirical model specification

The dynamic panel model using the GMM approach was specified where one lag of the dependent variable is incorporated in the model as regressor y_{it-1}

$$y_{it} = X_{it}\boldsymbol{\beta} + \rho y_{it-1} + \alpha_i + u_{it} \text{ for } t = 2,\ldots,T \text{ and } i = 1,\ldots,N \tag{2}$$

Taking the first difference of the equation to eliminate the individual effects

$$\Delta y_{it} = y_{it} - y_{it-1} = \Delta X_{it}\beta + \rho\Delta\, y_{it-1} + \Delta u_{it} \text{ for } t = 3,\ldots,T \text{ and } i = 1,\ldots,N. \tag{3}$$

If the coefficient of α_i varies over time, differencing the equation will not eliminate the individual impact. The equation may be reformulated as:

$$\Delta y = \Delta R\pi + \Delta u. \tag{4}$$

Applying the formula for the efficient GMM estimator, which is

$$\pi_{\mathrm{EGMM}} = [\Delta R' Z(Z'\Omega Z)^{-1} Z'\Delta R]^{-1} \Delta R' Z(Z'\Omega Z)^{-1} Z'\Delta y \tag{5}$$

Where Z is the instrument matrix for ΔR

A criterion for employing an additional set of moment requirements was established by Blundell and Bond (1998). In limited sample sizes, the additional moment conditions might improve the Arellano-Bond estimator's performance.

They advised specifically utilising the current circumstances.

$$\mathrm{E}(\Delta y_{it-1}(\alpha_i + u_{it})) = 0 \text{ for } t \geq 3 \tag{6}$$

These conditions for an additional instant are legitimate under the terms outlined in their paper. This situation permits the formulation of the complete set of moment conditions:

$$\mathrm{E}(Z_{SYS,i}^T P_i) = 0 \tag{7}$$

where

$$P_i = \begin{pmatrix} \Delta u_i \\ u_{i3} \\ u_{i4} \\ u_{i5} \\ \vdots \end{pmatrix} \tag{8}$$

and

$$Z_{SYS,i} = \begin{pmatrix} Z_{di} & 0 & 0 & 0 \\ 0 & \Delta y_{i2} & 0 & 0 \\ 0 & 0 & \Delta y_{i3} & 0 \\ 0 & 0 & 0 & \ddots \end{pmatrix}. \tag{9}$$

Thus, the dynamic panel model specification allows for the inclusion of lagged dependent variables as independent variables, which can help to control for unobserved heterogeneity and serial correlation in the data. The empirical model is estimated using five models which are used to test the hypothesis of the study. The models are estimated as follows:

3.6.1.1 Relationship between FinTech adoption, financial literacy and financial inclusion

For this financial inclusion model, the effect of financial literacy (FinL) on the financial inclusion index (FinII) was estimated and the moderating effect of the FinTech adoption index (FinAI) on the relationship between financial literacy and financial inclusion index was also estimated in the same model as follows:

$$FinII_{it} = \alpha_0 + \alpha_1 FinII_{it-1} + \alpha_2 FinL_{it} + \alpha_3 M_{it} + \sum_{i=2}^{N} \alpha_i X_{it} + \delta_i + \delta_t + \varepsilon_{it} \qquad (11)$$

Where i represent individual SSA countries at year t. α_0 is the constant, $FinII_{it}$ is the financial inclusion index for individual i SSA countries at year t. $FinL_{it}$ signifies financial literacy of individual i SSA countries at year t. M_{it} is the moderating variables FinTech adoption index for individual i SSA countries at year t. X_{it} represent control variables (educational attainment, income level, access to technology) for individual i SSA countries at year t. $\alpha_1 - \alpha_3$ are the coefficients of the variables in the model. δ_i Moreover, δ_i is a country-fixed effect used to depict the variations between individuals which remain static over time. δ_t denotes the year-fixed effect, employed capture variables that are static with individuals, but alter with time. ε_{it} is the error term.

3.6.1.2 Relationship between FinTech adoption, financial stability, financial inclusion and climate change

Climate change model is estimated focusing on the effect of the financial stability index (FinSI) on the climate change index (CChI) and the moderating FinTech adoption (FinAI) as follows:

$$CChI_{it} = \lambda_0 + \lambda_1 CChI_{it-1} + \lambda_2 FinII_{it} + \lambda_3 M_{it} + \lambda_4 M_{it} + \sum_{i=3}^{N} \lambda_i X_{it} + \delta_i + \delta_t + \varepsilon_{it} \qquad (12)$$

Where i represent individual SSA countries at year t. λ_0 is the constant, $CChI_{it}$ is climate change index for individual i SSA countries at year t. $FinII_{it}$ signifies financial inclusion index of individual i SSA countries at year t. M_{it} is the moderating variables FinTech adoption index and financial stability index for individual i SSA countries at year t. X_{it} represent control variables (political stability, access to technology, trade openness) for individual i SSA countries at year t. $\lambda_1 - \lambda_4$ are the coefficients of the variables in the model. δ_i Moreover, δ_i is a country-fixed effect used to depict the variations between individuals which remain static over time. δ_t denotes the year-fixed effect, employed capture variables that are static with individuals, but alter with time. ε_{it} is the error term.

3.6.1.3 Association between economic growth, climate change and financial stability

As estimated in the financial inclusion index model, the financial stability model also follows the same approach with the effect of the climate change index (CChI) on the financial stability index (FinSI) estimated together with the moderating effect on economic growth (GDPGR) on this association.

$$FinSI_{it} = \beta_0 + \alpha_1 FinSI_{it-1} + \beta_2 CChI_{it} + \beta_3 M_{it} + \sum_{i=2}^{N} \beta_i X_{it} + \delta_i + \delta_t + \varepsilon_{it} \qquad (13)$$

Where i represent individual SSA countries at year t. β_0 is the constant, $FinSI_{it}$ is the financial stability index for individual i SSA countries at year t. $CChI_{it}$ signifies financial literacy of individual i SSA countries at year t. M_{it} is the moderating variables FinTech adoption index for individual i SSA countries at year t. X_{it} represent control variables (political stability, access to technology, trade openness) for individual i SSA countries at year t. $\beta_1 - \beta_3$ are the coefficients of the variables in the model. δ_i Moreover, δ_i is a country-fixed effect used to depict the variations between individuals which remain static over time. δ_t denotes the year-fixed effect, employed capture variables that are static with individuals, but alter with time. ε_{it} is the error term.

3.6.1.4 Relationship between financial stability, FinTech and climate change

The relationship between the FinTech adoption index (FinAI) and climate change index (CChI) is estimated with the moderating influence of the financial stability index (FinSI) as follows:

$$CChI_{it} = \varpi_0 + \varpi_1 CChI_{it-1} + \varpi_2 FinAI_{it} + \varpi_3 M_{it} + \sum_{i=2}^{N} \varpi_i X_{it} + \delta_i + \delta_t + \varepsilon_{it} \qquad (14)$$

Where i represent individual SSA countries at year t. ϖ_0 is the constant, $CChI_{it}$ is climate change index for individual i SSA countries at year t. $FinAI_{it}$ signifies FinTech adoption index of individual i SSA countries at year t. M_{it} is the moderating variables FinTech adoption index for individual i SSA countries at year t. X_{it} represent control variables (political stability, access to technology, trade openness) for individual i SSA countries at year t. $\varpi_1 - \varpi_3$ are the coefficients of the variables in the model. δ_i Moreover, δ_i is a country-fixed effect used to depict the variations between individuals which remain static over time. δ_t denotes the year-fixed effect, employed capture variables that are static with individuals, but alter with time. ε_{it} is the error term.

3.6.1.5 Relationship between financial development, regulatory quality, economic growth and financial stability

The joint moderating influence of financial development and regulatory quality on the nexus between economic growth and financial stability is estimated as follows:

$$FinSI_{it} = \eta_0 + \eta_1 FinSI_{it-1} + \eta_2 GDPGR_{it} + \eta_3 M_{it} + \eta_4 M_{it} + \sum_{i=3}^{N} \eta_i X_{it} + \delta_i + \delta_t + \varepsilon_{it} \qquad (15)$$

Where i represent individual SSA countries at year t. η_0 is the constant, $FinSI_{it}$ is financial stability index for individual i SSA countries at year t. $GDPGR_{it}$ signifies gross domestic growth rate of individual i SSA countries at year t. M_{it} is the moderating variables financial development and regulatory quality for individual i SSA countries at year t. X_{it} represent control variables (political stability, access to technology, trade openness) for individual i SSA countries at year t. $\eta_1 - \eta_4$ are the coefficients of the variables in the model. δ_i Moreover, δ_i is a country-fixed effect used to depict the variations between individuals which remain static over time. δ_t denotes the year-fixed effect, employed capture variables that are static with individuals, but alter with time. ε_{it} is the error term.

3.6.2 Static panel models

The study utilizes a dynamic panel model to explore the relationship between the study variables. However, it suggests that employing a static model could offer additional insights. The static model provides an additional estimation beyond the dynamic baseline, offering a snapshot of the lasting equilibrium connections among the variables regardless of their previous fluctuations. This is beneficial for understanding the long-term impacts of FinTech integration on financial inclusivity, potentially revealing trends that the dynamic model may overlook. By comparing results from both models, the study aims to identify dynamic impacts that showcase the evolving influence of FinTech on inclusivity and predict potential long-term consequences. The static model can also be used to validate primary findings by incorporating time-invariant factors not explicitly considered in the dynamic framework. Therefore, the study employed the Fixed-Effects and Random-Effects Model under the static model.

3.6.3.1 Fixed effect model

A fixed effects model is commonly used in statistics to analyse panel data, which involves data collected from multiple entities over time. Unlike other models, fixed effects models assume that model parameters are constant values, in contrast to treating them as random variables. This approach is beneficial for panel data analysis as it accounts for unobserved heterogeneity, which refers to inherent differences among entities that remain consistent over time but vary across entities. These differences can impact the relationship between independent and dependent variables, potentially distorting results. To address these latent variations, fixed effects models incorporate group-specific or individual-specific effects as fixed parameters, representing enduring differences among entities. By assigning average values of the dependent variable to each entity across different periods, fixed effects in panel data often represent subject-specific means. The inside estimator or fixed effects estimator is a technique used to estimate the parameters of a model with fixed effects. This method involves removing the entity-specific mean from each observation, effectively eliminating individual-specific effects from the data. This adjustment helps reduce bias from unobserved variations, allowing for an unbiased evaluation of the remaining variables.

The assumptions underlying the FE model state that when examining the linear unobserved effects model for periods denoted as N observations and T, respectively:

$$k \times 1 \text{ for } t = 1, \ldots, T \text{ and } i = 1, \ldots, N \tag{16}$$

where,

y_{it} is the observed dependent variable for individuals i at time t.

X_{it} regressor vector for an individual i at a time t that is time-variant and $\ddot{X}$ (where k represents the number of independent variables).

β is the $k \times 1$ matrix representing the independent variable parameters.

α_i is an unobserved time-invariant effect on an individual i.

u_{it} is the error term denoting the individual i at time t.

Unlike X_{it}, α_i cannot be directly observed.

In contrast to the random effects model, which operates under the assumption that the unobserved individual effect α_i for each person (i) and period (t) is independent of all regressors X_{it}, the fixed effects (FE) model allows for the possibility of a relationship between α_i and the regressors. The error term u_{it} is subject to strict exogeneity. This suggests that there should be no correlation between the error term and either the independent variables or the individual effects.

Since α_i is unobservable, direct control over it is not feasible. The FE model removes individual-specific effects by transforming the variables through α_i demeaning.

$$y_{it} - \bar{y}_i = \left(X_{it} - \bar{X}_i\right)\beta + \left(\alpha_i - \bar{\alpha}_i\right) + \left(u_{it} - \bar{u}_i\right) \Rightarrow \ddot{y}_{it} = \ddot{X}_{it}\beta + \ddot{u}_{it} \tag{17}$$

Where $\bar{y}_i = \frac{1}{T}\sum_{t=1}^{T} y_{it}, \bar{X}_i = \frac{1}{T}\sum_{t=1}^{T} X_{it}, \bar{X}_i = \frac{1}{T}\sum_{t=1}^{T} X_{it}$ and $\bar{u}_i = \frac{1}{T}\sum_{t=1}^{T} u_{it}$. (18)

Since α_i is constant, the average $\overline{\alpha_i} = \alpha_i$ thereby eliminates the impact. The fixed effects estimator $\hat{\beta}_{FE}$ is derived using an ordinary least square (OLS) regression of the double-dotted variable y on the double-dotted variable $\ddot{X}$.

Thus, the empirical models are stated as follows:

$$FinII_{it} = \alpha_0 + \alpha_1 FinL_{it} + \alpha_2 M_{it} + \alpha_3 Controls_{it} + \mu_{it} \tag{19}$$

$$CChI_{it} = \lambda_0 + \lambda_2 FinII_{it} + \lambda_3 M_{it} + \lambda_4 M_{it} + \alpha_5 Controls_{it} + \mu_{it} \tag{20}$$

$$FinSI_{it} = \beta_0 + \beta_1 CChI_{it} + \beta_2 M_{it} + \beta_2 Controls_{it} + \mu_{it} \tag{21}$$

$$CChI_{it} = \varpi_0 + \varpi_1 FinAI_{it} + \varpi_2 M_{it} + \varpi_3 Controls_{it} + \mu_{it} \tag{22}$$

$$FinSI_{it} = \eta_0 + \eta_2 GDPGR_{it} + \eta_3 M_{it} + \eta_4 M_{it} + \eta_5 Controls_{it} + \mu_{it} \tag{23}$$

Where i represent individual SSA countries at year t. $\alpha_0, \lambda_0, \beta_0, \varpi_0$ and η_0 are the constants, the $FinII_{it}$, $CChI_{it}$, $FinSI_{it}$ is financial inclusion, climate change and financial stability indices respectively for individual i SSA countries at year t. $FinL_{it}$ and $GDPGR_{it}$ signify financial literacy and gross domestic growth rate of individual i SSA countries at year t. M_{it} is the moderating variables (FinTech adoption index, economic growth, financial stability, financial stability, regulatory quality) for individual i SSA countries at year t. $Controls_{it}$ represent control variables (educational attainment, income level, access to technology, Changes in income distribution, political stability) for individual i SSA countries at year t. $\alpha_1 - \alpha_3, \lambda_1 - \lambda_5, \beta_1 - \beta_3, \varpi_1 - \varpi_3, \eta_0 - \eta_5$ are the coefficients of the variables in the models. μ_{it} is the error term.

3.6.2.2 Random effect model

A random effects (RE) model, also known as a variance components model, is a statistical framework where model parameters are considered random variables. This model is used to analyse data from hierarchical structures with distinct populations, each having unique characteristics corresponding to their hierarchical level. RE models are a type of mixed effects model that can account for latent variability in the data, assuming that this variability remains constant over time and is unrelated to the independent variables being studied. These models are particularly useful for analyzing longitudinal data that includes persistent variability across multiple observations for an individual. Researchers may use differencing methods to manage this continuous heterogeneity by removing time-invariant components from the model. RE modelling relies on two key assumptions about individual-level effects: the RE assumption and the fixed effects assumption. The random effects assumption suggests that unobservable variations among individuals do not impact the independent variables being studied. In contrast, the fixed effects assumption implies that an individual's characteristics are influenced by the independent variables, highlighting the relationship between observable factors and personal traits.

The dependent variable Y_{it} is the jth independent variable at the ith unit. A straightforward way to model this variable is

$$Y_{ij} = \mu + U_i + W_{ij} + \epsilon_{ij}, \tag{24}$$

The dependent variable is denoted by μ. It includes unit-specific random effects U_i to quantify the discrepancy between the dependent variable and a specific unit, as well as individual-specific random effects W_{ij} to capture deviations of individual data points within a unit $i, e.,$. The model can be further expanded by incorporating explanatory variables to explain variations in scores across different categories.

The model can be improved by incorporating additional explanatory variables to account for variations in scores among different groups. This is stated as follows:

$$Y_{ij} = \mu + \beta_1 \mathrm{X}_{ij} + \beta_2 \mathrm{X}_{ij} + U_i + W_{ij} + \epsilon_{ij},$$

Thus, the empirical RE models are estimated as follows:

$$FinII_{it} = \alpha_0 + \alpha_1 FinL_{it} + \alpha_2 M_{it} + \alpha_3 Controls_{it} + \nu_{it} \tag{25}$$

$$CChI_{it} = \lambda_0 + \lambda_2 FinII_{it} + \lambda_3 M_{it} + \lambda_4 M_{it} + \alpha_5 Controls_{it} + \nu_{it} \tag{26}$$

$$FinSI_{it} = \beta_0 + \beta_1 CChI_{it} + \beta_2 M_{it} + \beta_2 Controls_{it} + \nu_{it} \tag{27}$$

$$CChI_{it} = \varpi_0 + \varpi_1 FinAI_{it} + \varpi_2 M_{it} + \varpi_3 Controls_{it} + \nu_{it} \tag{28}$$

$$FinSI_{it} = \eta_0 + \eta_2 GDPGR_{it} + \eta_3 M_{it} + \eta_4 M_{it} + \eta_5 Controls_{it} + \nu_{it} \tag{29}$$

Where i represent individual SSA countries at year t. $\alpha_0, \lambda_0, \beta_0, \varpi_0$ and η_0 are the constants, the $FinII_{it}$, $CChI_{it}$, $FinSI_{it}$ is financial inclusion, climate change and financial stability indices respectively for individual i SSA countries at year t. $FinL_{it}$ and $GDPGR_{it}$ signify financial literacy and gross domestic growth rate of individual i SSA countries at year t. M_{it} is the moderating variables (FinTech adoption index, economic growth, financial stability, financial stability, regulatory quality) for individual i SSA countries at year t. $Controls_{it}$ represent control variables (educational attainment, income level, access to technology, Changes in income distribution, political stability) for individual i SSA countries at year t. $\alpha_1 - \alpha_3, \lambda_1 - \lambda_5, \beta_1 - \beta_3, \varpi_1 - \varpi_3, \eta_0 - \eta_5$ are the coefficients of the variables in the models. ν_{it} is the error term.

After the estimation of both models, the Difference in coefficients will then be computed. Thus, the difference in coefficients between the FE and RE models will be calculated using the following formula:

$$d = \beta_{FE} - \beta_{RE} \tag{30}$$

where β_{FE} is the coefficient estimate from the fixed-effects model and β_{RE} is the coefficient estimate from the random-effects model.

The variance of the difference in coefficients will be calculated using the following formula:

$$V_d = \left(V_{FE} - V_{RE}\right) \big/ T \tag{31}$$

where V_{FE} and V_{RE} are the variance-covariance matrices of the coefficient estimates from the fixed-effects and random-effects models, respectively, and *T* is the number of periods.

After computing the variance-covariance matrices, the test statistic will be calculated using the following formula:

$$H = d'(V_d)^{(-1)} d \tag{32}$$

where *d'* is the transpose of *d*.

Finally, the test statistic was compared to the critical value from the chi-squared distribution with degrees of freedom equal to the number of endogenous variables. If the test statistic is greater than the critical value, then the null hypothesis of no endogeneity is rejected in favour of the alternative hypothesis of endogeneity.

3.6.3 Sensitivity analysis and robustness check

It is imperative to conduct a sensitivity analysis to test the robustness of the results. This involves testing the model with different specifications and comparing the results. This can help identify the most robust results and increase confidence in the findings. Therefore, the study performed a multiple-case sensitivity analysis to check the robustness of the GMM results. To ensure the robustness of the study findings, the study conducted a sensitivity analysis using two main approaches:

employing alternative econometric methods and including additional control variables in the model. The discussion on the use of alternative econometric methods and inclusion of additional control variables are as follows:

3.6.3.1 Sensitivity analysis and robustness check using alternative econometric methods

Using alternative econometric methods is a common approach in sensitivity analysis to test the robustness of the results. The FE and RE models are two commonly used alternative methods to estimate panel data models. The FE model assumes that the individual-specific effects are constant over time and are correlated with the independent variables (Gujarati, 2018). This method can control for unobserved heterogeneity across individuals and reduce the potential endogeneity bias. On the other hand, the RE model assumes that the individual-specific effects are uncorrelated with the independent variables. This method is useful when the individual-specific effects are unobservable or not of primary interest (Gujarati et al., 2004).

Comparing the results from the GMM approach to those obtained from the FE model or the RE model will provide insights into the robustness of the findings. If the results are consistent across different methods, this can increase confidence in the results. However, if the results are not consistent, this can indicate that the findings may be sensitive to the choice of the econometric method. Several studies have used alternative econometric methods to test the robustness of their findings. For example, Tadesse et al. (2017) used both the FE and RE models to estimate the determinants of agricultural technology adoption in Ethiopia. They found that the results were consistent across both methods, suggesting that their findings were robust to the choice of the econometric method. Therefore, in this study, comparing the results obtained from the GMM approach to those obtained from the fixed-effects model or the random-effects model will provide insights into the robustness of the findings and increase confidence in the results.

The sensitivity analysis is important because it helps to test the robustness of the results and ensure that the findings are not sensitive to changes in the model specification or sample size. A robust finding is consistent across different specifications and sample sizes. The sensitivity analysis is also important because it helps to identify potential weaknesses in the model and suggest areas for further research. Thus, sensitivity analysis is an important step in econometric analysis that helps to test the robustness of the results. By changing the specification of the model, testing alternative econometric methods, and testing the robustness of instruments, the sensitivity analysis helps to ensure that the results are not sensitive to changes in the model specification and that the findings are robust and reliable

The results generated from the estimates were reported. The results were presented in tables and graphs, with appropriate statistical measures such as standard errors and confidence intervals. The results were discussed about the research questions and hypotheses. The limitations and implications of the study are also discussed. Thus, the GMM approach is a powerful tool for analyzing the relationships between financial literacy, financial inclusion, climate change, economic growth, financial development, regulatory requirements, and financial stability in SSA countries. By following a rigorous and systematic procedure, the study obtained accurate and reliable results that can inform policy and practice in the SSA region.

3.6.3.2 Sensitivity analysis and robustness check by inclusion of additional control variables and alternative econometric methods

The study conducted a further sensitivity analysis and robustness testing to enhance the trustworthiness of the findings. Firstly, the random effects model was used to assess the sensitivity of the results. The study then go further by incorporating quantile regression, which provided a more understanding of the relationships among variables across different income brackets in SSA countries. This approach allowed for a nuanced analysis of how factors such as FinTech implementation impact financial inclusion differently based on income levels (Ariansyah et al., 2023).

Furthermore, the Gini index as a control variable was incorporated in all models to account for income inequality's potential influence on the examined relationships. By doing so, the study mitigated the impact of this confounding variable, strengthening the reliability of the identified associations among economic growth, financial stability, financial literacy, inclusion, climate change, and income inequality (Zhang et al., 2023). The study's robustness assessment involved a stratified approach that progressed from the random effects model to quantile regression and the inclusion of the Gini index. This comprehensive approach provided policymakers in SSA with empirically supported insights into the interconnections between key variables, offering a reliable foundation for decision-making.

Thus, the empirical RE models are estimated as follows:

$$FinII_{i\tau} = \alpha_{0\tau} + \alpha_{1\tau}FinL_i + \alpha_{2\tau}M_i + \alpha_{3\tau}Controls_i + \varepsilon_{i\tau} \quad (26)$$

$$CChI_{i\tau} = \lambda_{0\tau} + \lambda_{2\tau}FinII_i + \lambda_{3\tau}M_i + \lambda_{4\tau}M_i + \alpha_{5\tau}Controls_i + \varepsilon_{i\tau} \quad (27)$$

$$FinSI_{i\tau} = \beta_{0\tau} + \beta_{1\tau}CChI_i + \beta_{2\tau}M_i + \beta_{2\tau}Controls_i + \varepsilon_{i\tau}$$

(28)

$$CChI_{i\tau} = \varpi_{0\tau} + \varpi_{1\tau}FinAI_i + \varpi_{2\tau}M_i + \varpi_{3\tau}Controls_i + \varepsilon_{i\tau} \quad (29)$$

$$FinSI_{i\tau} = \eta_{0\tau} + \eta_{2\tau}GDPGR_i + \eta_{3\tau}M_i + \eta_{4\tau}M_i + \eta_{5\tau}Controls_i + \varepsilon_{i\tau} \quad (30)$$

Where i represent individual SSA countries. $\alpha_{0\tau}, \lambda_{0\tau}, \beta_{0\tau}, \varpi_{0\tau}$ and $\eta_{0\tau}$ are the constants at quantile τ, the $FinII_i$, $CChI_i$, $FinSI_i$ is financial inclusion, climate change and financial stability indices respectively for individual i SSA countries. $FinL_i$ and $GDPGR_i$ signify financial literacy and gross domestic growth rate of individual i SSA countries. M_i are the moderating variables (FinTech adoption index, economic growth, financial stability, financial stability, regulatory quality) for individual i SSA countries.

$Controls_i$ represent control variables (educational attainment, income level, access to technology, Changes in income distribution, political stability) for individual i SSA countries. $\alpha_{1\tau} - \alpha_{3\tau}, \lambda_{1\tau} - \lambda_{5\tau}, \beta_{1\tau} - \beta_{3\tau}, \varpi_{1\tau} - \varpi_{3\tau}, \eta_{1\tau} - \eta_5$ are the coefficients of the variables in the models at quantile τ. $\varepsilon_{\tau i}$ is the error term.