Chapter 3 - Research Methodology

3.1 Data and Methodology

This research employs a quantitative research methodology, utilizing primary data collected through field research. The primary data is gathered directly from respondents through the design and administration of a structured questionnaire tailored to address the research objectives. The collected data is then subjected to statistical analysis to validate hypotheses and draw meaningful conclusions. By focusing on empirical evidence, the approach ensures objective and measurable insights, enabling the study to produce reliable and generalizable findings. The target population includes working individuals aged 18 and above from the BTR by conducting on-site visits to workplaces. Prior permissions were obtained, and schedules were carefully coordinated with workplace authorities to minimize disruptions. During the data collection phase from September 2023 to December 2023, as an approach to randomization, a respondent was first randomly selected from the employees available at a given workplace on the day of data collection. Following this initial selection, every alternate employee was subsequently included in the sample. This systematic method, initiated with a random starting point, ensured an unbiased and representative selection of respondents while maintaining simplicity and practicality in the sampling process. To ensure equitable representation across multiple workplaces and to maintain manageability in data collection, a restriction was imposed limiting the selection to a maximum of 10 respondents per workplace on any given day. This restriction was designed to prevent overrepresentation of any single workplace while allowing for sufficient diversity in the sample. This randomization protocol was consistently applied across all data collection activities to ensure methodological rigor. Each workplace was visited at least twice, with a minimum interval of seven days between visits. This strategy accounted for potential variations in employee attendance and workplace dynamics on different days, effectively minimizing selection bias and enhancing the reliability and validity of the collected data. Kokrajhar was strategically chosen as the study area due to its role as the administrative centre of the BTR and its representation of individuals from all four districts: Chirang, Baksa, Udalguri, and Kokrajhar. As the administrative headquarters, Kokrajhar serves as a focal point for governance, commerce, and social services, making it an ideal location to capture a diverse range of perspectives.

The selection of Kokrajhar allows the study to reflect the experiences of individuals from various parts of the BTR, providing insights into the multifaceted nature of retirement financial behaviour across different segments of society. Kokrajhar's strategic location also facilitates access to people from surrounding districts who frequently travel for work or services. Additionally, its significance as an administrative hub positions it as a likely site for the implementation of policies and programs related to financial literacy and retirement preparedness.

By focusing on Kokrajhar, the study aligns with the goal of achieving generalizability, ensuring that the sample reflects the broader BTR population. The findings can thus be confidently applied to other areas in the region, offering valuable insights for policymakers and stakeholders. This focus enhances the relevance of the research, contributing to the ongoing discussion on improving financial literacy and retirement preparedness. Kokrajhar's accessibility, diversity, and administrative importance make it an ideal study area, enriching the data and ensuring the applicability of the research findings across the BTR.

Guided by Onwuegbuzie and Collins (2007), the research adopts a stratified purposive sampling method, a sampling strategy that is particularly effective for targeting specific subgroups within a population. In this case, the focus is on two distinct groups: employed individuals (encompassing private, government, and public sector employees) and self-employed individuals (including businesspersons, professionals, and gig workers) in Kokrajhar. This deliberate choice of sampling technique is especially advantageous in investigating retirement financial behaviour because it enables a comprehensive exploration of the financial behaviour, perspectives, and challenges associated with these different occupational backgrounds. The stratified purposive sampling method ensures that the sample is not only representative of different employment sectors but also allows for a deeper analysis of how varying income structures, job security levels, and access to financial resources impact individuals' financial planning for retirement. Employed individuals, particularly those in government and public sector jobs, are often beneficiaries of pension schemes and retirement benefits. These benefits, which provide a steady stream of income post-retirement, may influence their attitudes toward retirement savings and investment strategies. For instance, they may have a lower perceived need for personal retirement savings, as the pension system may provide a safety net. This contrasts with self-employed individuals, who typically lack access to employer-sponsored retirement plans. As a result, they often must independently navigate the complexities of managing their retirement savings, including deciding on appropriate investment vehicles and strategies for wealth accumulation. These distinct financial realities could lead to vastly different retirement financial behaviour, making it essential to analyze both groups separately.

Incorporating self-employed individuals into the study, particularly businesspersons, professionals, and gig workers, adds a layer of novelty to the research. Gig workers, who represent a growing segment of the workforce in the contemporary labour market, operate outside traditional employment structures and often face unique financial challenges. Their incomes are typically fluctuating, and they are generally without the safety net of employer-sponsored retirement plans. This lack of stability, coupled with the absence of institutional support for retirement planning, creates distinct challenges that could affect how gig workers approach retirement saving. Investigating the financial behaviour and planning strategies of gig workers allows the study to shed light on how this rapidly evolving sector of the workforce is adapting to the challenges of long-term financial security. This analysis provides valuable insights into the strategies and coping mechanisms that gig workers employ, contributing to a broader understanding of retirement financial behaviour. The stratified purposive sampling method enhances the analytical rigor of the research. Policymakers and financial educators can design tailored interventions to address the unique challenges faced by each group, thereby improving the effectiveness of retirement planning programs. By adopting a stratified purposive sampling approach, the research not only ensures the inclusion of diverse perspectives but also allows for a more in-depth understanding of the factors influencing retirement financial behaviour. The findings can contribute to the development of more inclusive financial policies and education programs that address the unique needs of both employed and self-employed individuals, including gig workers. Ultimately, this sampling strategy provides the research with a solid foundation for drawing conclusions that are not only relevant but also highly actionable for improving retirement outcomes across a wide range of occupational groups.

When conducting a survey-based study, determining an appropriate sample size is crucial to ensuring the reliability and validity of the results. According to Krejcie and Morgan (1970) and Cochran (1977), a minimum sample size of 384 responses is generally recommended for large population sizes at an alpha level of 0.05. This threshold is based on statistical considerations that ensure sufficient power to detect meaningful differences or relationships within the data, especially in large populations. It reflects the need for a robust sample to obtain representative and accurate findings that can be generalized to the larger population. Isaac and Michael (1995) note that larger sample sizes are necessary in these cases to ensure that each sub-group is adequately represented. In addition to the general sample size recommendations for large populations, Weisberg and Bowen (1977) emphasize that for studies analyzing demographic variables (categorical data) as sub-samples, each subgroup should have a minimum sample size of 100. This guideline ensures that each subgroup is adequately represented in the study. A minimum sample size of 100 per subgroup is essential for ensuring that the findings for each demographic variable are statistically reliable and can provide meaningful insights. In total, 653 working individuals from the Kokrajhar district participated in the study. To determine the appropriate sample size, we utilized G*Power analysis software, inputting an effect size of 0.05 (f-square), an α error probability of 0.05, and a power of 0.95 while considering eight predictive variables. This analysis indicated that a minimum sample size of 262 respondents was necessary, confirming the adequacy of our sample size.

The final sample of 641 after eliminating incomplete responses exceeds this minimum requirement, providing a robust foundation for the study's analyses. The primary data collected for the purpose of the research is described in Table 3.1.

Table 3.1 Summary of the Dataset

Variables	Categories	Observations	Percentage (%)
Age	18 to 29 years	213	33.2
	30 to 39 years	210	32.8
	40 to 49 years	121	18.9
	50 to 59 years	82	12.8
	60 years and above	15	2.3
Gender	Male	431	67.2
	Female	210	32.8
Annual income	Up to Rs 2,50,000	310	48.4
	Rs 2,50,001 to Rs 5,00,000	163	25.4
	Rs 5,00,001 to Rs 10,00,000	103	16.1
	Above Rs 10,00,000	65	10.1
Education	Up to Matriculation	69	10.8
	Higher Secondary/Diploma	123	19.2
	Graduate	252	39.3
	Post-graduate	168	26.2
	Above post-graduate	29	4.5
Marital status	Single	226	35.3
	Married	408	63.7

	Divorced	7	1.1
Number of children	No children	300	46.8
	1 child	182	28.4
	2 children	127	19.8
	More than 2 children	32	5
Caste	Scheduled Tribe	382	59.6
	General	134	20.9
	Scheduled caste	34	5.3
	Other Backward Classes	91	14.2
Type of employment	Government	124	19.3
	Public sector	105	16.4
	Private Sector	104	16.2
	Business	102	15.9
	Professionals	102	15.9
	Gig Workers	104	16.2

Source: Researcher's Survey

The dataset outlined in Table 3.1 presents a comprehensive overview of the respondents' characteristics across various socio-economic and demographic variables. This table offers insights into respondents' age distribution, gender, income levels, education, marital status, family size, caste, and employment types. Each of these categories contributes to understanding the population's diversity and provides valuable context for interpreting the broader results of the study.

The dataset includes respondents spanning a wide range of age groups, divided into five categories. The age group of 18 to 29 years is the largest, with 213 respondents, accounting for 33.2% of the sample. Close behind, the 30 to 39 years category includes 210 respondents, or 32.8% of the sample, making these two age groups the most represented. This prevalence of younger and middle-aged adults indicates a relatively youthful sample. The 40 to 49 years age group comprises 18.9% of the respondents, followed by 12.8% in the 50 to 59 years bracket. The smallest group, 60 years and above, has only 15 respondents, representing 2.3% of the sample.

Males make up 67.2% of the sample with 431 respondents, while females comprise 32.8%, totaling 210 respondents. The predominance of male respondents suggests a possible male-dominant sample or a scenario in which men may be more represented in the occupational groups surveyed.

Income levels among respondents show considerable diversity, segmented into four categories. Nearly half of the respondents, 48.4%, report an annual income of up to Rs 2,50,000, representing the largest income category with 310 respondents. The next income bracket, Rs 2,50,001 to Rs 5,00,000, includes 163 respondents or 25.4% of the sample. Income levels between Rs 5,00,001 and Rs 10,00,000 make up 16.1% with 103 respondents, while the smallest income category, above Rs 10,00,000, comprises 10.1% of the sample with 65 respondents. The concentration of respondents in the lower-income brackets suggests that a substantial portion of the sample represents lower- to middle-income earners, which could have implications for economic behaviour, lifestyle choices, and purchasing power.

The educational background of the respondents is diverse, with the majority holding either graduate or higher qualifications. Graduates form the largest group with 252 respondents, accounting for 39.3% of the sample. Following this, post-graduates represent 26.2%, with 168 respondents, indicating that over two-thirds of the sample possess at least a graduate degree. Respondents with Higher Secondary or Diploma qualifications account for 19.2%, while those with education up to Matriculation comprise 10.8%. A smaller proportion, 4.5%, holds qualifications above post-graduate level. This level of education among respondents suggests a relatively well-educated sample, which may influence the study outcomes if education impacts opinions or behaviour related to the subject matter.

Marital status is another significant demographic, with the majority of respondents being married. Out of the total sample, 408 respondents, or 63.7%, report being married. The single respondents constitute 35.3%, while a very small percentage, 1.1%, are divorced. This distribution shows a predominance of married individuals, which could be relevant in studies focusing on family or social dynamics.

Examining family size, particularly the number of children among respondents, provides insight into family demographics. Respondents with no children represent the largest group, making up 46.8% of the sample, or 300 respondents. Those with one child constitute 28.4%, with 182 respondents. Respondents with two children represent 19.8%, and those with more than two children account for 5.0%. The high percentage of respondents without children might correlate with the younger age distribution, as younger individuals may not yet have started families, or it may reflect broader demographic trends.

Caste composition is an important demographic feature within the dataset. Scheduled Tribe (ST) respondents make up the majority at 59.6%, or 382 individuals, indicating a significant representation from this group. General category respondents account for 20.9%, Scheduled Caste respondents are 5.3%, and Other Backward Classes represent 14.2%. This demographic breakdown suggests a sample where ST are highly represented, which is reflective of the region's population demographics or the focus of the study on communities with higher ST populations.

The dataset provides a breakdown of respondents' employment types, with six distinct categories. Government employees represent 19.3%, with 124 respondents. Public sector workers account for 16.4% of the sample, closely followed by the private sector, which comprises 16.2% of respondents. Both business owners and professionals constitute 15.9% each, and gig workers also represent 16.2% of the sample. This diversity in employment types reflects a workforce engaged in various sectors, with a notable presence of government, public, and private sector employees, as well as individuals involved in business, professional fields, and the gig economy. The gig workers' presence aligns with current trends in non-traditional employment arrangements.

This dataset presents a diverse and multifaceted demographic profile, encompassing a range of factors such as age, income, education, employment types, and social dynamics. The respondents are largely young to middle-aged individuals, predominantly male, and spread across varying income categories, with a notable concentration in the lower-income brackets. Educationally, the majority are graduates or post-graduates, indicating a relatively educated sample. A significant portion of respondents are married, with many having no children, which may align with younger age groups. Additionally, the caste distribution is skewed towards ST respondents, reflecting the region's demographic makeup. Employment is varied, with substantial representation from government, private sector, and gig economy workers. The demographic diversity across these variables offers a broad perspective, enriching the study by enabling analysis across multiple socio-economic dimensions. The concentration of lower-income earners and a younger, educated workforce are significant factors likely to shape the insights derived from this sample. The dataset's range of age groups—from 18 to over 60—enables an exploration of how retirement financial behaviour may shift across the lifespan. The larger representation of younger and middle-aged individuals, who are economically active, provides insights into workforce dynamics and current consumption patterns. The varied educational backgrounds allow for a deeper analysis of how education impacts financial decision-making, employment trends, and family responsibilities. Given the high percentage of respondents with higher education, the dataset reflects a relatively informed population, enhancing the credibility of the study's findings. The well-distributed income categories allow for an exploration of economic differences, especially in how income influences spending habits, lifestyle choices, and financial challenges, particularly within lower-income households. The dataset also captures various employment types, including government, public, private, business, professional, and gig economy workers. This diversity allows comparisons of job stability, satisfaction, and economic resilience across different work forms. Additionally, the marital status and family size data enable exploration of how family dynamics influence decisions in areas like financial planning and health.

However, there are some limitations that we observe. The underrepresentation of individuals aged 60 and above (just 2.3%) may limit insights into the elderly's needs, such as retirement and healthcare. Additionally, nearly half of the respondents fall within the lowest income bracket, which may skew findings towards the financial challenges faced by lower-income households. The high representation of ST and Other Backward Classes respondents reflects regional demographics and may not be fully generalizable across India. Furthermore, the overrepresentation of highly educated individuals could limit the generalizability to populations with lower educational levels.

Overall, while this dataset provides a rich foundation for analysis, acknowledging its strengths and limitations is essential for interpreting the findings within the context of its specific demographic and socio-economic composition. The dataset's diversity offers several advantages in terms of representation and potential for nuanced insights, making it a valuable resource for exploring socio-economic factors in the BTR region.

The design of this study is methodologically rigorous and strategically targeted. This careful consideration guarantees a sufficient sample size to detect meaningful differences across groups, providing reliable insights into the retirement financial. The study's findings are poised to contribute significantly to the understanding of retirement preparedness within the BTR. The research can inform future financial education policies and resources tailored to the diverse workforce demographics in the region. The implications of these findings extend beyond academic interest; they hold practical relevance for policymakers, financial educators, and community organizations working to enhance financial literacy and retirement preparedness among working adults in the BTR. We have employed Analysis of Variance (ANOVA) (Moorthy et al., 2012, Ostertagova, 2014 and Kim, 2017) as the analytical approach to investigate the influence of demographic variables on retirement financial behaviour among working individuals in the BTR. ANOVA is a widely used statistical method for examining mean differences across multiple groups, making it particularly well-suited to studies involving categorical independent variables, like demographic attributes. The decision to use ANOVA is grounded in the categorical nature of demographic characteristics, such as age, income, education level, and others outlined in our dataset. These variables are divided into specific groups or levels—for instance, age is grouped into categories like 18–29, 30–39, 40–49, and so forth, while education is categorized into levels such as "Up to Matriculation," "Higher Secondary," "Graduate," "Post-graduate," and "Above Post-graduate." ANOVA is particularly effective in simultaneously comparing these groups, allowing us to determine whether significant differences in retirement financial behaviour exist across these demographic categories. This approach provides valuable insights into how each demographic factor may uniquely influence retirement financial behaviour, helping to identify potential areas where certain groups exhibit distinct tendencies. ANOVA is an effective choice for our study as it is efficient in examining differences between multiple groups in a single test rather than conducting multiple t-tests between each pair of groups. This makes it well-suited for our study, as we aim to compare retirement financial behaviour across several demographic categories simultaneously. This statistical approach enables us to analyze multiple demographic factors systematically. It allows us to assess each factor individually to see if differences in retirement financial behaviour are significant across groups (e.g., does behaviour differ across age brackets or education levels?). By applying ANOVA, we gain a robust understanding of whether demographic factors are significantly associated with retirement financial planning behaviour.

To ensure the robustness of our findings, we employ both parametric and non-parametric forms of ANOVA. This decision is guided by the assumptions underlying each method. Demographic factors often yield data that may not meet all the assumptions of parametric ANOVA (Kim ,2017), and by incorporating non-parametric alternative, we increase the validity and reliability of our analysis. The parametric ANOVA approach is suitable when specific assumptions are met, including:

a. **Normality**: The data within each group should be normally distributed.

b. **Homogeneity of Variance**: The variances across the groups should be approximately equal.

c. **Independence of Observations**: Each observation should be independent of the others.

When these assumptions hold, parametric ANOVA offers more statistical power, making it more sensitive in detecting differences between groups. To begin , we will use parametric ANOVA for its robustness and reliability in estimating group differences in normally distributed data with balanced variances.

In cases where assumptions of normality or homogeneity of variances are violated, non-parametric alternatives provide an ideal solution. These include tests like the Kruskal-Wallis Test for one-way analysis which do not rely on the same assumptions as parametric ANOVA. Kruskal-Wallis Test is a non-parametric alternative to One-Way ANOVA and is useful for comparing groups when the dependent variable is ordinal or when the data do not meet the normality assumption. This test ranks data and compares the median rank scores of each group rather than the means. It provides a robust means of analyzing differences across groups when data are not normally distributed or when variances are unequal. The use of non-parametric ANOVA methods is justified when our demographic data deviates from the normal distribution or exhibits unequal variances. For example, income or education levels are often skewed, with a few individuals at very high or very low levels, and categories like employment type yield unequal group sizes. In such cases, non-parametric ANOVA provides the flexibility to analyse group differences without relying on stringent parametric assumptions, making it especially suitable for real-world data with more variability. By incorporating both parametric and non-parametric approaches, we ensure a rigorous analysis that accommodates the nature of the data and its potential violations of parametric assumptions. The use of both methods strengthens our findings by providing corroborative evidence across different statistical approaches. This analytical strategy enhances the robustness of our study, allowing for nuanced and reliable insights into how diverse demographic groups within the BTR approach their financial planning for retirement. The findings from this analysis will contribute to understanding how demographic characteristics influence retirement financial behaviour, aiding in the development of more targeted financial planning resources and policies for working individuals in the region.

The literature reveals a well-established division between data-driven and theory-based approaches. Quantitative studies often employ econometric models to analyze financial data, while others use experimental designs to evaluate the impact of policy changes on retirement planning behaviour. For example, Hershey and Mowen (2000) utilized SEM to explore financial preparedness for retirement, linking financial knowledge and personality traits—such as conscientiousness and retirement involvement—to planning behaviour. Hershey et al.

(2007) expanded this approach cross-culturally, incorporating social and cultural factors to show how psychological and environmental elements influence retirement planning in varied contexts. Hershey et al. (2007) further refined this model, demonstrating that socio-cultural differences also play a crucial role in shaping retirement behaviour.

Theory-based research draws on established frameworks like the Theory of Planned Behaviour (Ajzen, 1991) and the Theory of Reasoned Action (Fishbein, 1979). With technological advancements, the Technology Acceptance Model (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003) have also been applied to retirement planning research to understand how external factors, such as technology, affect financial decision-making. These studies are often hypothesis-driven, aiming to provide theoretical insights into how socio-cultural, psychological, and external factors shape financial preparedness across diverse socio-economic contexts.

Quantitative studies are predominant in this field, employing methods like multiple regression (Petkoska and Earl, 2009; Gathergood, 2012), logistic regression (Fisher and Montalto, 2010), hierarchical regression (Jacobs-Lawson and Hershey, 2005), and complex techniques such as Generalized Method of Moments regression (Van Rooij et al., 2011; Brown and Taylor, 2014). SEM has been instrumental in analyzing retirement behaviour, allowing researchers to model direct and indirect relationships. Studies by Hershey and Mowen (2000), Hoffmann and Broekhuizen (2010), and more recently Tomar et. al., (2021) have employed SEM to analyse retirement planning, emphasizing the method's utility in exploring complex financial behaviour.

Quantitative methods, including path modelling, hierarchical regression, and mediation analysis, have yielded valuable insights into the predictors of retirement financial behaviour. For example, Bapat (2020) and Ramalho et al. (2018) used PLS-SEM to examine the multidimensional aspects of financial planning, while other studies have implemented mediation analysis (e.g., Tang and Baker, 2016) and interpretive structural modelling to deepen the understanding of financial preparedness.

This research employs a quantitative approach to understanding retirement financial behaviour by analyzing survey responses from the BTR in Assam using PLS-SEM and multigroup analysis. PLS-SEM is well-suited to exploring complex causal relationships between latent variables and is particularly beneficial in small-sample studies, which focuses on a specialized population (Hair et. al, 2019). Its multigroup analysis capabilities also facilitate comparisons between groups, enabling the study to uncover differences in retirement financial behaviour across various subgroups.

It may be noted that multivariate data analysis techniques such as multiple regression, logistic regression, and analysis of variance have become foundational in empirical research, allowing for the testing of hypothesized relationships among variables (Haenlein & Kaplan, 2004). These methods have been applied across a broad spectrum of scientific disciplines, significantly contributing to our understanding of complex phenomena. However, they exhibit three key limitations. First, these techniques typically operate on simplified models that include one layer of dependent and independent variables, limiting their capacity to assess complex causal sequences like “A leads to B leads to C” or intricate networks of interconnected variables. This constraint can compromise the quality of results, especially when studying systems with multiple intermediary variables (Sarstedt et al., 2020). Second, first-generation techniques generally focus on observable variables and require unobservable theoretical constructs to be validated separately, usually through confirmatory factor analysis. This need for post hoc validation can introduce potential weaknesses when incorporating abstract theoretical measures. Third, these traditional methods assume that variables are measured without error, yet this ideal condition is rarely achieved in practice, especially when dealing with latent constructs like perceptions or attitudes, where both systematic and random measurement errors are common.

Given these limitations, researchers have increasingly adopted advanced methodologies such as SEM to account for more complex relationships, measurement errors, and latent constructs. SEM enables the simultaneous modelling and estimation of intricate interdependencies among multiple variables, and it is particularly well-suited to handling unobservable theoretical constructs through indirect indicators (Cole & Preacher, 2014). SEM also accounts for measurement errors, enhancing the accuracy of estimations for abstract variables.

Two main SEM approaches—covariance-based SEM (CB-SEM) and partial least squares SEM (PLS-SEM)—have become prominent. CB-SEM focuses on evaluating theoretical models by assessing their fit with observed data, providing a way to confirm or disconfirm hypotheses. In contrast, PLS-SEM, often described as a “causal-predictive” approach, emphasizes variance explanation in dependent variables rather than model fit, making it more suitable for exploratory research (Jöreskog & Wold, 1982; Chin et al., 2020). Over the past few decades, introductory and review articles have expanded the methodological landscape of SEM, with researchers examining the applications of PLS-SEM across various disciplines and exploring its methodological implications, including author networks and citation trends (Hwang et al., 2020).

In SEM path models, constructs or latent variables are represented as circles, while directly measurable variables are shown as rectangles. Arrows indicate directional relationships, suggesting predictive links based on theoretical foundations. A typical PLS path model comprises two components: the structural model (inner model), which represents relationships among constructs, and the measurement model (outer model), which connects constructs with their indicators. This modelling process also incorporates error terms, acknowledging unexplained variance within the estimation.

PLS-SEM is particularly valuable for complex, exploratory research settings. It can handle small sample sizes, a significant advantage when data is limited, and it avoids distributional assumptions, making it robust to non-normal data. Additionally, it accommodates various measurement scales (e.g., metric, ordinal, binary) and can handle complex models with both reflective and formative indicators. However, PLS-SEM does not permit circular relationships, which aids in the clarity of causal interpretations. The method’s focus is on explaining variance rather than model fit, a difference from CB-SEM, and allows researchers to assess the predictive capability and validity of measurement constructs rather than imposing traditional fit indices (Hair et al., 2011).

In studies on financial behaviour, PLS-SEM is particularly useful due to its flexibility with sample sizes, predictive orientation, and ability to model complex relationships, including both direct and indirect effects between latent constructs. While CB-SEM typically aims to confirm established theories, PLS-SEM excels in exploratory analyses, making it ideal for examining dynamic fields such as retirement financial behaviour, where psychological, socioeconomic, and demographic factors interact intricately. The choice of PLS-SEM for analyzing retirement financial behaviour in the BTR of Assam addresses both practical and conceptual needs. Conceptually, retirement financial behaviour is shaped by numerous interdependent factors, including financial literacy, psychological traits and demographic factors. PLS-SEM enables the modelling of these multifaceted influences and captures both direct and indirect relationships among variables. Practically, PLS-SEM is robust in scenarios with small to medium sample sizes and complex latent constructs, making it ideal for specialized populations such as the BTR, where sample collection can be challenging. By using PLS-SEM, this study can uncover critical insights into how various factors affect retirement financial behaviour across a culturally unique population.

A notable strength of PLS-SEM is its ability to conduct multigroup analysis. It allows for a comparison of model structures and path coefficients across different segments. In the context of this study, multigroup analysis helps identify variations in retirement financial behaviour among financial literacy subgroups. This segmentation is essential for understanding how factors like financial knowledge, or individual psychological traits influence retirement financial behaviour differently across age or income groups. The multigroup approach not only provides detailed insights but also enables targeted policy recommendations tailored to the unique needs of each subgroup.

In practice, the PLS-SEM procedure starts with developing a measurement model, which includes defining and validating latent constructs. Constructs are validated using tests for convergent and discriminant validity to ensure they accurately measure the intended concepts. Evaluating the measurement model is crucial to ensure that the constructs and their corresponding indicators (items) are reliable and valid (Hair et. al., 2019). In this study, the measurement model was evaluated using PLS regression with Smart PLS 4.0 to assess both the uni-dimensionality of the constructs and their psychological antecedents related to retirement financial behaviour. PLS is favored in this context due to its ability to simultaneously measure latent variables and test relationships between them (Tomar et.al, 2021 and Babin et. al.,2008). We followed a two-step approach for model evaluation: first, we assessed the outer measurement model to establish the constructs' uni-dimensionality, reliability, and validity. This ensures that the constructs used in the inner model were measured accurately (Hair et al., 2014). Next, we evaluated the inner structural model to examine the causal relationships between the latent constructs based on significant path coefficient values (Hair et al., 2014).

In assessing the measurement model, the initial step was to evaluate the internal consistency of the items or variables, which reflects the proportion of variance a variable share with its latent construct (Götz et. al., 2010 and Tomar et. al. ,2021). A common guideline is to seek loadings of 0.7 or higher, as this suggests the construct explains more of the shared variance relative to the error variance (Hulland, 1999). However, Hulland (1999), recommend a lower threshold of 0.5 for factor loadings when adapting items from other settings. Nunnally (1978) supports this approach by advocating the exclusion of items with lower loadings, as they contribute minimally to the model’s explanatory power. Consequently, we removed items with factor loadings below 0.5. To assess construct reliability, we utilized both Cronbach's alpha and composite reliability, which help ensure that items within each construct are strongly related. Cronbach's alpha examines uni-dimensionality within multi-item scales (Cronbach, 1951), while composite reliability evaluates the degree to which items represent their respective constructs (Hair et. al.,2019 and Jöreskog, 1971). Following the recommended threshold of 0.7 for both Cronbach's alpha and composite reliability, as suggested by Nunnally and Bernstein (1994) and Tomar et al. (2021), our analysis confirms the reliability of the constructs. It may be noted that reliability values between 0.60 and 0.70 are considered "acceptable" in exploratory research, while values between 0.70 and 0.90 are considered to range from "satisfactory to good (Hair et. al, 2019). To ensure the quality of the proposed model, we assessed both convergent and discriminant validity. Convergent validity was evaluated using factor loadings, composite reliability, and the average variance extracted (AVE) values. AVE measures the variance captured by all items within a construct, with a value above 0.5 signifying convergent validity or uni-dimensionality (Hair et. al., 2010). Discriminant validity complements convergent validity by ensuring that sets of items measure conceptually distinct constructs. Discriminant validity refers to the extent to which constructs that are supposed to be distinct are, in fact, different from each other. Discriminant validity, a counterpart to convergent validity, ensures that distinct constructs are captured by separate sets of items, reinforcing their conceptual distinction. This differentiation means that each item set reflects a unique dimension rather than a common underlying factor (Henseler et. al, 2009). Traditionally, discriminant validity has been evaluated using the Fornell-Larcker criterion. The Fornell-Larcker criterion is a statistical approach used to evaluate discriminant validity within a measurement model, ensuring that constructs are distinct and do not excessively overlap. Discriminant validity is achieved when the square root of the Average Variance Extracted (AVE) for a construct is greater than the correlations between that construct and all other constructs in the model. However, Henseler et. al., (2015) advocate for a more accurate method in PLS-SEM: the heterotrait-monotrait ratio (HTMT). HTMT assesses discriminant validity by comparing the average correlation of items across different constructs (heterotrait-heteromethod) with the average correlation within the same construct (monotrait-heteromethod) (Henseler et al., 2015). HTMT values below 0.9 indicate adequate discriminant validity (Hair et; al., 2017; Henseler et al., 2015). The HTMT ratio is a method to assess discriminant validity, with values closer to 1 suggesting that the constructs are highly correlated, which could indicate a lack of discriminant validity.

Further, to assess the structural model's reliability, the first step is to examine multicollinearity to ensure that predictor variables do not excessively overlap, which could undermine model validity. The Variance Inflation Factor (VIF) is commonly used for this purpose, with values below 3 considered acceptable to avoid multicollinearity issues, though some studies suggest that issues can occur even at this level (Mason and Perreault, 1991; Becker et al., 2015). Values closer to 3 or lower are ideal for reliable assessment (Hair et. al, 2019). Model fit measures are used to assess how well a structural model represents the data (Hussain et al., 2018; Hair et al., 2019; Tomar et al., 2021). One commonly used measure is the Standardized Root Mean Square Residual (SRMR), which evaluates the difference between observed and predicted correlations. A lower SRMR value indicates a better fit, with values below 0.08 indicating a good fit, values between 0.08 and 0.10 indicating a fair fit, and values above 0.10 suggesting a poor fit. The saturated model serves as a baseline, representing a perfect fit with no restrictions, while the estimated model, based on theoretical assumptions and data, includes hypothesized relationships and paths. The goal is to determine how well the estimated model approximates the data, and although the estimated model does not fit as well as the saturated model, this is expected, as the saturated model is unrestricted and provides a perfect fit, while the estimated model is constrained by theoretical assumptions. The R-square (R^2) values reflect the proportion of variance in each construct that is explained by the predictor variables, providing valuable insight into the explanatory power of the model. According to Chin (1998) and Henseler et al. (2009), R^2 values are typically categorized as substantial, moderate, and weak in PLS path modeling, with thresholds of 0.67, 0.33, and 0.19, respectively. These benchmarks help assess the strength of the relationships between variables and the overall model fit.

The f-square (f^2) values assess the impact of each exogenous construct on its corresponding endogenous construct, reflecting the effect size of predictors within the model (Hussain et al., 2018). To calculate f^2, the R-square value of the model is compared when a specific predictor is included versus when it is removed, enabling an evaluation of the predictor's relative importance. According to Cohen’s guidelines (1988), f-square values of 0.02, 0.15, and 0.35 are interpreted as representing weak, moderate, and strong effects, respectively.

The Q^2 predict value is an essential metric for evaluating the predictive relevance of a PLS path model, integrating both in-sample explanatory power and out-of-sample prediction (Geisser, 1974; Stone, 1974; Shmueli et al., 2016). The blindfolding procedure, used to calculate Q^2, involves removing individual data points, imputing them with the mean, and then estimating the model parameters. This approach predicts the removed data points for all variables, with smaller differences between predicted and original values indicating higher predictive accuracy (Sarstedt et al., 2017). As a general guideline, Q^2 values greater than zero suggest predictive accuracy for the corresponding endogenous construct, with values higher than 0, 0.25, and 0.50 representing small, medium, and large predictive relevance, respectively (Sarstedt et al., 2017).

Once validated, the model specifies paths to test direct and indirect relationships among constructs, with hypotheses framed around the effects of demographic and psychological variables on retirement financial behaviour. The assessment of direct effects and indirect effects is fundamental in understanding the mechanisms underlying the relationships between variables in a given model. Direct effects and indirect effects refer to the different pathways through which an independent variable (IV) influences a dependent variable (DV). The direct effect represents the unmediated relationship between the IV and DV, while the indirect effect captures the influence of the IV on the DV through one or more mediator variables. A notable strength of PLS-SEM is its capability to perform multigroup analysis, a technique that allows researchers to compare model structures and path coefficients across different demographic segments. In the context of this study on retirement financial behaviour in the BTR, multigroup analysis facilitates understanding variations in retirement financial behaviour among different subgroups. After estimating the model, multigroup analysis is applied to compare how path relationships differ across high and low financial literacy subgroups. The application of PLS-SEM with multigroup analysis allows for a nuanced exploration of retirement financial behaviour, illuminating specific challenges and opportunities for varying literacy level within the BTR. This approach not only deepens understanding within a localized context but also contributes broadly to financial behaviour research by demonstrating how a methodological blend of PLS-SEM and multigroup analysis can capture the intricate socio-economic dynamics of retirement financial behaviour. Through these insights, this study can inform culturally appropriate financial education initiatives and policies to better support diverse populations in their retirement preparedness.

3.2 Measuring Retirement Financial Behaviour

Retirement financial behaviour refers to the decision's individuals make to secure their financial future after leaving the workforce. The retirement financial construct was developed by adapting items from two established scales: the Retirement Planning Behaviour (RPB) scale by Moorthy et al. (2012) and the Retirement Savings Behaviour (RSB) scale by Jacobs-Lawson and Hershey (2005). This construct aims to comprehensively assess proactive retirement financial behaviour, including planning and saving, to capture an individual's preparedness for retirement.

The RPB component evaluates individuals' attitudes and concerns about their retirement readiness. Key items include statements such as "I am concerned about the state of my financial preparation for my retirement" (RPB1), "I am confident that I will have a decent standard of living in my retirement" (RPB2), and "At present, I rate my financial preparation for retirement as good" (RPB3). Additionally, RPB4 ("I expect my standard of living in retirement will decrease") addresses potential concerns about lifestyle adjustments in retirement, offering insights into respondents' expectations. Item RPB5 ("I am not confident that I could work out what my expected income and expenditure would be in retirement") addresses confidence in projecting retirement income and expenditures.

The RSB component focuses on actual saving practices, measuring the extent to which individuals have engaged in saving efforts for retirement. This includes items such as "Made meaningful contributions to a voluntary retirement savings plan" (RSB1), "Relative to my peers, I have saved a great deal for retirement" (RSB2), "Accumulated substantial savings for retirement" (RSB3), "Made a conscious effort to save for retirement" (RSB4), and "Based on how I plan to live my life in retirement, I have saved accordingly" (RSB5). These items collectively provide a detailed view of both the attitudes and concrete actions individuals have taken toward securing their financial future.

Exploratory factor analysis (EFA) is a statistical technique used to identify underlying latent constructs (factors) within a set of observed variables by grouping them into factors based on shared variance (Hair et al., 2010). An EFA was conducted to refine and validate the measurement items, resulting in an 8-item scale that provides a robust measure of behaviour related to retirement planning and saving. This unified factor shall be referred to as "retirement financial behaviour" for the purpose of the research. The scale provides a comprehensive yet focused approach to measuring how individuals anticipate and act upon their financial needs for retirement, offering a valuable tool for analyzing retirement financial behaviour. The EFA results are presented in Table 3.2. The rotated component matrix presents the factor loadings following Principal Component Analysis (PCA) with Varimax rotation, which is commonly used to achieve simpler, more interpretable results by maximizing the variance of squared loadings for each factor. This matrix shows the loadings of each item on the two extracted components, reflecting the correlation of each item with each factor. In the analysis, two primary components emerged, indicating distinct dimensions within the retirement financial behaviour construct.

Table 3.2 EFA Results

Item	Component 1	Component 2
RPB1	0.588	
RPB2	0.740	
RPB3	0.739	
RPB4		0.842
RPB5		0.78
RSB1	0.723	
RSB2	0.784	
RSB3	0.823	
RSB4	0.655	
RSB5	0.798	

Source: Researcher's Analysis

Component 1 includes items RPB1, RPB2, RPB3, RSB1, RSB2, RSB3, RSB4, and RSB5, with loadings ranging from .588 to .823. Items in this component predominantly represent proactive planning and savings behaviour, capturing both attitudes toward and actions taken in retirement preparation. Notably, items RSB3 (.823) and RSB5 (.798) exhibit particularly strong loadings, emphasizing substantial savings accumulation and retirement-focused financial contributions.

Component 2 is defined by items RPB4 and RPB5, with high loadings of .842 and .780, respectively. These items relate to individuals' expectations of their retirement living standards, suggesting a focus on lifestyle adjustments post-retirement.

This two-component solution, achieved after three iterations, implies that the retirement financial behaviour construct encapsulates both proactive financial actions and an anticipated adjustment in lifestyle, with each component reflecting specific facets of retirement financial behaviour. The use of Varimax rotation and Kaiser normalization optimizes the clarity of these components, providing a structured foundation for further analysis.

This unified factor shall be referred to as "retirement financial behaviour" for the purpose of the research. The scale provides a comprehensive yet focused approach to measuring how individuals anticipate and act upon their financial needs for retirement, offering a valuable tool for analyzing retirement financial behaviour.