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# THE TRANSFORMATIVE IMPACT OF BUSINESS INTELLIGENCE ON UNEMPLOYMENT INSURANCE: ENHANCING DECISION MAKING AND OPERATIONAL EFFICIENCY THROUGH A MIXED-METHODS APPROACH

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**Abstract**

Background: The increasing complexity and demands of Unemployment Insurance (UI) systems necessitate innovative approaches to enhance Decision Making (DM) and Operational Efficiency (OE). Business Intelligence (BI) offers potential solutions by providing data-driven insights that can transform the administration of UI. This study examines the impact of BI on UI, focusing on DM as a mediator and OE as a moderator, within the framework of the Resource-Based View (RBV) theory.

**Methods:** A mixed-methods approach was employed, combining quantitative and qualitative data. Surveys were administered to UI professionals to collect quantitative data, which were analyzed using regression, mediation, and moderation techniques. Qualitative data were gathered through interviews and focused on a valuable approach. These qualitative methods allow us to explore participants' perspectives, experiences, and opinions in depth. into BI applications in UI operations.

**Results:** The findings indicate that BI significantly enhances DM capabilities, leading to improved administration of UI. DM was found to mediate the relationship between BI and UI effectiveness. Furthermore, OE was identified as a significant moderator, strengthening the positive impact of BI on UI outcomes

**Conclusion:** This study demonstrates that BI can be a strategic resource for public sector services, particularly in enhancing the performance of UI systems. By investing in BI tools and training, UI agencies can leverage data-driven DM to achieve greater efficiency. The approach enriches the analysis, providing a comprehensive view of BI's transformative impact. Future research should explore longitudinal effects and broader applications across different public service domains.

**Keywords:** Unemployment Insurance, Decision Making, Operational Efficiency, Business intelligence

## 1. **Introduction**

Digital transformation and the persistent importance of information as a critical success factor influence all business sectors, including insurance, today. In an era dominated by big data, businesses are compelled to analyze and utilize data profitably [1]. New analytics techniques and visualizations enable companies to enhance current business operations and attract new clients [2]. However, without suitable correlation or visualization, large data volumes offer no immediate practical use, merely representing raw information. Thus, competitive advantages stem from rapid and high-quality data processing [3]. BI systems facilitate this processing and are thus considered valuable technologies within insurance firms. Through statistical and visualization tools, data volumes can be processed and analyzed for business objectives. BI is particularly relevant to financial services firms as they are technology-driven, collect extensive customer data, and can profitably leverage this information in various ways [4]. Overall, there are numerous potential BI applications [5].

UI is a vital social welfare program designed to assist individuals who have been laid off without any personal illegal behavior. By providing temporary financial support, UI helps alleviate the economic impact of unemployment on individuals and families, while also stabilizing the economy during downturns. However, administering UI programs faces several challenges, such as inefficiencies, delays in claim processing, and the need for accurate and timely DM to prevent fraud and ensure fair benefit distribution [6]. BI offers a transformative solution to these issues. BI encompasses a variety of technologies. It enables organizations to make informed decisions by providing insights from vast data sets. In the UI context, BI can enhance DM processes, improve OE, and ultimately optimize system effectiveness [7]. DM is crucial in any organization and must be well-planned, comprehensive, transparent, and secure to address problems effectively [8]. Decision Support Systems (DSS) utilize analytical information to influence DM. Recent research on DSS and expert systems, which incorporate these analytical tools, aims to evaluate optimal decisions and consider them as part of a comprehensive environment supporting efficient information processing based on a thorough understanding of the problem's structure [9]. BI employed by organizations should align with the business context or DM environment in which it is utilized; this alignment is crucial for BI's success [10]. This may be because the link between decision quality and BI capabilities has not been extensively studied. This relationship is critical because BI's primary goal is to support organizational DM [11, 12]. This study aims to explore the transformative collision of BI on UI systems. By applying the RBV theory, which asserts that an organization's resources and capabilities are essential for achieving competitive advantage, this research examines how BI acts as a strategic resource that can enhance UI outcomes. particularly, the study investigates the following objectives:

1. To assess the direct impact of BI on DM within UI systems.
2. To evaluate the mediating role of DM in the affiliation between BI and UI outcomes.
3. To examine the moderating effect of OE on the affiliation between BI and UI outcomes.

By tackling these goals, this study aims to add value to both theoretical and practical domains. On a theoretical level, it broadens the use of the RBV model in the public sector, showcasing how BI can be used as a strategic resource to improve organizational performance. On a practical level, the research offers valuable insights for policymakers and administrators regarding the advantages of incorporating BI into UI systems. It underscores how BI can resolve inefficiencies, enhance service provision, and ultimately support the socio-economic welfare of unemployed individuals.

Research Questions

To achieve the objectives of this study, the following research questions are formulated:

1. How does the implementation of BI tools influence DM processes in UI programs?
2. In what ways does DM mediate the relationship between BI and the effectiveness of UI programs?
3. How does BI impact the OE of UI administration?
4. To what extent does OE moderate the relationship between BI and UI program outcomes?

This paper is divided into multiple sections to methodically address the research questions and goals. After this introduction, a thorough literature review will be conducted to examine existing research on UI, BI, DM, and OE. The review will also discuss the RBV theory, which forms the foundation of this research the theoretical construct and proposition formulation segment will present the guiding principles of this investigation, elaborating on the proposed interconnections among the factors. The procedure segment will describe the investigative structure, data-gathering methods, and participant selection employed to examine the propositions used to test the hypotheses. The results section will offer a comprehensive analysis of the data, including descriptive statistics, hypothesis testing, and mediation and moderation analyses. The discussion section will interpret the findings, emphasizing their implications for theory and practice, while recognizing the study's limitations and proposing areas for future research. Finally, the conclusion will recap the key findings, contributions, and recommendations derived from the study.

## 2. Theoretical Background

### *2.1Underpinning Theory*

#### *The Resource-Based View*

RBV, as described by [13], posits that competitive advantage is attainable through the provision of unparalleled services to customers. The core focus of existing literature is the strategic comprehension of how resources are utilized to gain a competitive edge within an organization [14]. International business theorists argue that the success and failure of organizations in various environments can be understood by examining their competitive tactics and partnership establishment in growing economies. The regional insight offered by partnerships is vital for crafting value in alignment with local preferences alliances are crucial for conceptualizing value according to local demands [15]. RBV posits that resources serve as inputs in an organization's production activities and can be classified into organizational resources. A capability refers to the ability of a set of resources to execute a specific task or function [16]. Every organization possesses unique resources and capabilities essential for achieving specific returns. In the competitive landscape of the 21st century, organizations are characterized by evolving capabilities under dynamic management to attain above-average results. Consequently, organizations are driven by specific resources and capabilities rather than industry structures over time [16]. The theory elucidates the impact of organizational resources, such as human and financial resources, on organizational performance. The importance of RBV in this study lies in its connection between organizational capabilities and performance equipped with suitable human and finance resources poised for superior outcomes. Therefore, the RBV theory is significant for both personnel and financial competencies in this suggested research [17]. RBV offers a valuable framework for comprehending the strategic significance of BI in UI programs. According to RBV, organizations secure a competitive advantage. In the UI context, BI is seen as a valuable resource that enhances DM and OE. By incorporating BI into their operations, UI agencies can develop unique capabilities that improve their performance and service delivery. This study will apply the RBV theory to investigate how BI contributes to the strategic goals of UI programs, focusing on the mediating role of DM and the moderating role of OE.

## 2.2UI

Unemployment is a widespread issue with significant effects on individuals, businesses, and governments. Over the past twenty years, our understanding of the personal experience of unemployment has greatly expanded. UI is a social welfare initiative aimed at providing temporary financial aid to those who have lost their jobs without fault and who meet specific eligibility requirements. The goals of UI are to offer economic stability, assist in re-employment, and lessen the negative impacts of unemployment on both the economy and individuals. Despite its crucial role, UI programs encounter problems such as fraudulent claims, inefficient processing systems, and delays in distributing benefits, underscoring the need for enhanced management and operational practices. Additionally, the difficulty in promptly detecting and addressing fraudulent claims further complicates the administration of UI programs. The advent of digital technologies and the growing availability of big data present opportunities to tackle these challenges [31].

## 2.3 Business Intelligence

BI encompasses technologies, applications, and practices aimed at presenting business data. The origins of BI can be traced back to the 1960s with the advent of DSS. Since then, BI has progressed from simple data management and reporting tools to sophisticated analytics and predictive modeling technologies. In the 1990s, data warehousing and online analytical processing (OLAP) became key elements of BI, allowing organizations to store vast amounts of data and execute complex queries efficiently. The 2000s introduced data mining and advanced analytics, enabling more refined data analysis and insight generation [32]. Today, BI includes a broad array of tools such as AI, ML, and big data analytics, which support real-time data processing and predictive insights. BI holds particular appeal for financial services companies due to their technology-driven nature and the extensive customer data they gather, which can be leveraged in multiple profitable ways. Overall, there are numerous potential applications for BI [5].

## 2.4 DM

DM is a fundamental managerial function involving the collection of the best option from multiple alternatives. Effective DM is essential for organizational success and heavily depends on the quality and timeliness of the available information [33]. DSS utilizes analytical information to impact DM. Recent studies on DSS and expert systems, which incorporate these analytical tools, aim to identify optimal decisions and consider them within a comprehensive framework that supports efficient information processing based on a deep understanding of the problem's structure [12]. Traditional DM theories, such as the Rational DM Model, propose that decisions are made through a structured and logical process, whereas Behavioral Decision Theory takes into account human cognitive limitations and biases [34].

## 2.5 OE

OE denotes an organization's capability to deliver goods or services efficiently while maintaining high-quality standards. It entails enhancing processes, optimizing resource allocation, and reducing inefficiencies [35]. OE holds significant importance in public sector operations such as UI programs, where resources are typically constrained, necessitating the prompt and precise delivery of services to beneficiaries.

## 3. Conceptual Framework and Hypothesis Development:

### 3.1 Conceptual research framework

The segment on the conceptual structure and hypothesis generation will describe the theoretical underpinnings of this study, clarifying the anticipated linkages between variables in UI systems with a focus on how BI enhances DM processes and OE. This study investigates the relationships involving BI (independent variable), UI performance (dependent variable), DM (mediator), and OE (moderator). This study's importance is entrenched in its prospective impact on academic literature and practical applications in public administration. By exploring the impact of BI on improving UI programs, this study provides insights into how data-driven DM and enhanced OE can lead to improved program outcomes. Additionally, the application of RBV theory offers a robust theoretical basis for understanding the strategic importance of BI in public sector organizations.

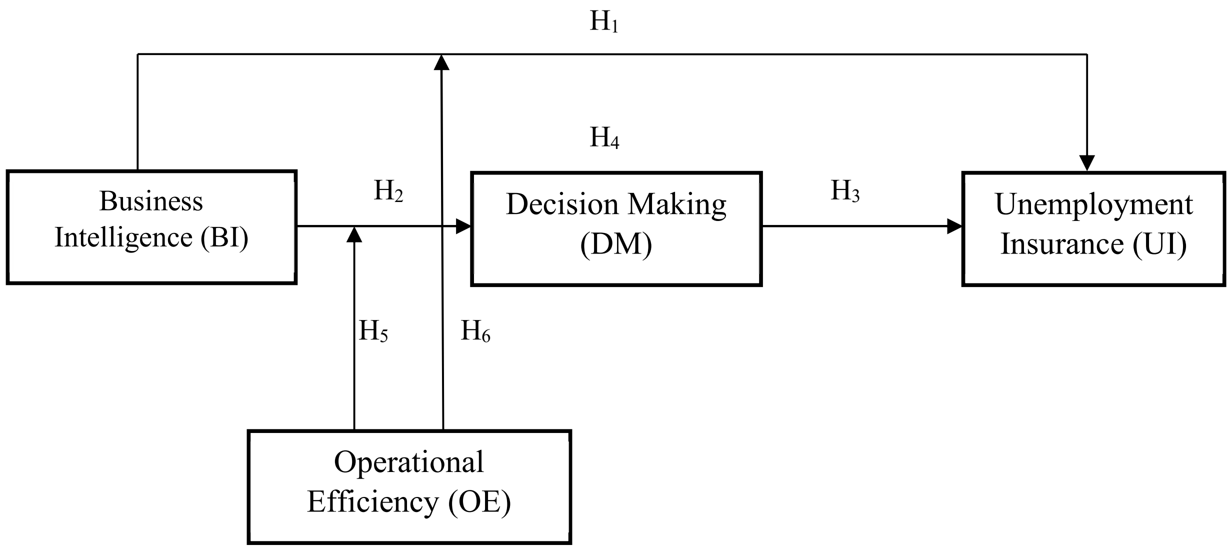


**Figure 1. Conceptual Research Framework**

### 3.2 Hypotheses development

#### *3.2.1BI and UI*

BI has emerged as a transformative technology across diverse sectors, including public administration. This proposition suggests that the incorporation of BI tools and methodologies directly enhances the efficacy of UI programs. BI encompasses various applications and technologies designed to present business data to enhance DM and OE [6, 7]. In the realm of UI, BI can elevate data management practices, deliver precise forecasting, and facilitate prompt identification of fraudulent activities, thereby improving the efficiency and effectiveness of benefit distributions. Efficient data management plays a pivotal role in administering UI programs, which handle extensive data related to claimants, employment histories, and financial transactions. BI tools streamline the integration and analysis of this data, enhancing accuracy and reducing duplication. For example, BI systems aggregate data from multiple origins into a centralized repository, ensuring coherence and enabling comprehensive analysis. Studies demonstrate that implementing BI in public sector entities enhances data precision and accessibility, critical for effective UI management [6, 12]. A notable advantage of BI lies in its capability to predict trends and anticipate future outcomes. UI programs are crucial for providing financial aid to unemployed individuals but are often criticized for inefficiencies stemming from paperwork, manual claims processing, and protracted verification procedures [18]. These processes not only delay benefit disbursements but also escalate administrative burdens on UI agencies. Additionally, identifying and rectifying fraudulent claims on time poses further challenges to UI program management. The advent of digital technologies and the ubiquity of big data present opportunities to tackle these issues [19]. By leveraging BI tools, UI administrators can augment data processing capabilities, enhance claims verification accuracy, and expedite DM procedures. This study aims to explore these potentials, focusing on BI's transformative impact within the UI context. BI's objective is to strengthen DM processes by furnishing stakeholders with actionable insights gleaned from data. BI tools encompass a broad spectrum of functionalities, encompassing data mining, predictive analytics, reporting, and dashboard creation [9]. Prior research underscores that BI tools furnish UI agencies with access to extensive, real-time data, empowering them to analyze trends, predict demand, and optimize resource allocation. As a result, BI is poised to enhance DM by equipping DM with actionable insights drawn from precise and timely information [31]. the hypothesis of the research is

*$H_1$: BI has a positive relationship with UI*

### *3.2.2Business Intelligence and Decision Making*

BI originated as an overarching term introduced by the Garner Group and researcher Howard Wisner in 1989. It encompasses a range of concepts and methodologies aimed at enhancing DM by leveraging event-based systems and processes. BI applications play a pivotal role in recalibrating organizational action plans to measure and achieve company goals and objectives accurately [20]. BI involves the tasks of gathering extensive datasets from internal operations and external entities. This function is supported by complicated instruments for swift evaluation and prediction, fostering prompt decision-making essential to corporate achievement [10]. BI frameworks merge data acquisition, data storage, and intellect management with analytic instruments to supply exhaustive insights into both market competition and internal dynamics to strategists and executives [10]. An analogy to the above definition suggests that BI systems deliver actionable information to decision-makers promptly and accurately, aiming to enhance the speed and quality of DM processes and facilitate management tasks. BI represents a natural evolution from previous DSS [11]. The emergence of data warehouses as repositories, the benefits of data cleansing for achieving a single source of truth, advancements in software and hardware capabilities, and the proliferation of Internet technologies as standard user interfaces have collectively strengthened BI beyond its historical limitations. BI aggregates information from diverse systems, transforming raw data into actionable insights and, through human analysis, into knowledge. BI furnishes strategic insights to decision-makers, enabling organizations to harness vast amounts of data to discern behavioral patterns among customers and competitors. This capability is instrumental in helping organizations tailor their plans and programs across various business facets such as production, distribution, pricing, and capacity planning [11]. According to the RBV, a company's resources are pivotal in determining its performance and can confer sustained competitive advantages in the marketplace [21]. [22] [23]. Therefore, the formulated hypothesis is

$H_2$: *BI has a positive relationship with Decision Making*

***3.2.3 Decision Making and UI***

The hypothesis proposing that DM positively correlates with UI asserts that improvements in DM processes directly enhance the outcomes of UI programs. Effective DM can streamline the processing of claims, reduce errors, and improve the accuracy of benefits distribution. A critical impact area of DM on UI programs lies in claim processing. Efficient DM ensures swift and precise processing of claims. This effectiveness decreases the likelihood of errors in administering UI benefits [24]. Errors may involve incorrect benefit calculations, improper disqualification of claimants, or delays in benefit disbursement. A U.S. Department of Labor report [25] underscored that states with robust DM frameworks reported fewer administrative errors and discrepancies in benefit distribution. By minimizing errors, UI programs can promptly and accurately deliver entitled benefits to eligible claimants, thereby enhancing overall program reliability and trustworthiness. Accurate benefit distribution is pivotal for UI program effectiveness. Well-informed decisions on eligibility and benefit amounts ensure fair and efficient resource allocation. This study exemplifies how enhanced DM processes can positively influence UI program efficiency and effectiveness. At the federal level, the U.S. Department of Labor has invested in DM technologies to enhance UI program administration. An assessment by the Government Accountability Office (GAO) [26] found that improved DM processes, supported by advanced data analytics and decision-support tools, resulted in more accurate benefit determinations and timely payments. Survey data indicated a statistically significant positive association between DM quality and key UI program performance indicators, including processing speed, error rates, and beneficiary satisfaction [27]. Effective DM processes enhance administrative efficiency by ensuring prompt and accurate claims processing. Therefore, the formulated hypothesis is

$H_3$ *DM has a positive relationship with UI*

***3.2.4 DM as a Mediator:***

The effectiveness of BI in enhancing UI programs manifests through improved DM processes. This indicates that BI's positive influence on UI outcomes stems from advancements in how decisions are formulated within these programs. BI tools augment DM capabilities, thereby fostering more efficient and effective UI programs. Within UI contexts, BI tools provide capabilities such as data analytics, real-time reporting, and predictive insights, all of which bolster DM quality. These enhanced DM processes consequently lead to enhancements across various facets of UI programs. Research demonstrates that organizations leveraging BI witness substantial enhancements in DM processes, crucial for effectively managing UI programs [28]. The enhancements in DM serve as the mechanism through which BI positively impacts the overall efficacy of UI programs. These findings underscore the pivotal role of DM in mediating the beneficial effects of BI on UI program outcomes. Enhanced data analysis capabilities are fundamental for making well-informed decisions that amplify the effectiveness of UI programs. A study referenced by [29] indicated that BI adoption for data analysis correlates with higher DM standards, which in turn contribute to superior program outcomes. DM acts as the conduit through which BI's influence on UI outcomes is actualized. According to RBV theory, BI resources empower UI agencies to make informed decisions regarding benefit eligibility, claims processing, and program assessment, thereby enhancing overall program effectiveness. Therefore, DM is anticipated to mediate the relationship between BI and UI outcomes [30]. These enhancements in DM processes mediate the favorable impact of BI systems on UI program effectiveness.

$H_4$: *DM mediates the positive relationship between BI and UI*

***3.2.5OEas a Moderator***

OE refers to an organization's capability to deliver services cost-effectively while maintaining high-quality and timely outcomes. In the context of UI programs, OE encompasses streamlined processes, reduced waste, efficient resource allocation, and prompt service delivery. A robust OE ensures that insights derived from BI tools are seamlessly integrated into DM processes. When OE is optimal, UI programs can effectively leverage BI insights [5, 6, and 7]. Effective operations entail established procedures for integrating data analytics into DM and adequately trained staff proficient in BI tool utilization. Such an environment maximizes BI's impact on DM, thereby enhancing overall program effectiveness. For example, a UI program with high OE can swiftly process claims and adjust benefit levels based on real-time data analytics, ensuring accurate and timely benefit distribution. Conversely, when OE is lacking [7], BI's positive impact on DM may diminish. Inefficient operations may stem from outdated processes, inadequate training, or insufficient resources for leveraging BI tools effectively. In such scenarios, BI insights may not be fully utilized, resulting in slower DM processes, increased error rates, and suboptimal program performance. Effective DM is crucial for efficiently administering UI programs [5, 2, 1]. Timely and accurate decisions are essential to promptly deliver benefits to eligible individuals and prevent approval of ineligible claims BI instruments are crucial in advancing decision-making procedures by granting UI managers immediate access to relevant information and practical knowledge. Conversely, Operational Excellence concentrates on an entity's proficiency in providing services economically and suitably. In the realm of UI, OE involves minimizing the time and resources required for claims processing and benefit distribution. Improving OE enables UI agencies to reduce administrative costs and enhance overall program effectiveness. This study seeks to explore the impact of BI on UI programs, specifically in enhancing DM and OE [7]. OE signifies UI agencies' capability to optimize resource utilization, cut costs, and improve service delivery. According to the RBV theory, BI enhances OE by automating manual facilitating informed resource allocation decisions. Therefore, OE is expected to moderate the relationship between BI and UI outcomes, thereby amplifying BI's benefits on UI program effectiveness [17]. This finding underscores the importance of

*$H_5$OE moderates the positive relationship with BI and DM*

*$H_6$OEmoderatesthe positive relationship between BI and UI*

## 4. Research Methodology

This segment details the analytical plan, demographic and sampling framework, methodologies for data acquisition, tools for measuring variables, and approaches for examining the gathered data employed in this inquiry.

**4.1.1 Mixed-Methods Approach**

The study employs a mixed-methods research design to comprehensively investigate the transformative impact of BI on UI. This approach allows for the triangulation of data from quantitative surveys and qualitative interviews, facilitating a deeper understanding of the research occurrence.

**Rationale for Choosing a Mixed-Methods Approach**

The integration of quantitative surveys and qualitative interviews enables a holistic examination of the complex relationships between BI, DM, OE, and UI outcomes. By triangulating data from different sources, the study enhances the validity and reliability of the findings, minimizing the limitations inherent in individual methods. Quantitative data provide statistical rigor and generalizability, while qualitative data offers the participants' experiences, motivations, and perceptions, enriching the interpretation of quantitative results. The use of multiple methods facilitates data validation through cross-validation and convergence of findings, strengthening the overall validity of the study.

**4.1.2 Quantitative Phase**

**i) Research Design and Sample Selection**

In the quantitative segment, a cross-sectional study format is utilized. Selective sampling methods will be applied to employ subjects from key players in UI oversight, such as the public sector, insurance companies, and educational entities. The extent of the sample will be calculated using statistical efficacy analysis principles to confirm sufficient representativeness and the generalizability of the outcomes.

**ii) Data Collection Methods**

Information will be gathered through organized surveys administered electronically. The survey instrument will be designed to capture information on participants' perceptions of BI utilization, DM processes, OE, and UI outcomes. Additionally, secondary data sources such as official UI program reports and administrative records will be accessed to supplement the survey data.

**iii) Measurement of Variables**

BI: Participants will be asked to rate the extent of BI implementation within their organizations using validated scales, measuring factors such as data integration, analytics capabilities, and decision support functionalities.

DM: Perceptions of DM effectiveness will be assessed through Likert-type scale items, capturing dimensions such as timeliness, accuracy, and alignment with organizational objectives.

OE: Participants will be asked to evaluate OE metrics, including processing time, resource utilization, and cost-effectiveness, on a Likert scale.

UI Outcomes: Objective measures of UI outcomes, such as claim processing accuracy, fraud detection rates, and customer satisfaction scores, will be collected from administrative records.

**iv) Data Analysis Techniques**

Quantitative data analysis will encompass descriptive statistics to summarize the characteristics of the sample and variables. Inferential statistics, including regression analysis, will be conducted to test the hypothesized relationships between BI, DM, OE, and UI results Mediation and moderation analyses will be performed to examine the indirect and conditional effects, respectively, of BI on UI outcomes.

**v) Statistical Techniques for Analysis**

Descriptive Statistics: Descriptive analysis will be conducted to summarize the characteristics of the sample and variables, including means, standard deviations, frequencies, and percentages.

Inferential Statistics: Regression evaluations will be applied to scrutinize the postulated interplays BI, DM, OE, and UI outcomes.

Mediation Analysis: Mediation analysis will be undertaken to examine the indirect influence of BI on UI outcomes through DM, utilizing methods like bootstrapping for significance determination of the indirect influence.

Moderation Analysis: Moderation analysis will be executed to investigate the moderating impact of OE on the relationship between BI and UI outcomes, using approaches such as hierarchical regression analysis to assess the interaction effect.

**4.2.2 Qualitative Phase**

**i) Research Design and Sample Selection**

In the qualitative phase, a phenomenological research design will be adopted to explore participants' lived experiences and perceptions related to BI implementation in UI administration. Purposive sampling will be employed to choose individuals who possess rich insights into the research phenomenon, ensuring diversity in perspectives and experiences.

**ii) Data Collection Methods**

Semi-structured interviews will be carried out with chosen individuals to elicit in-depth narratives and perspectives. The interview guideline will be crafted based on the conceptual framework and research objectives, covering themes such as BI adoption drivers, DM dynamics, operational constraints, and perceived impacts on UI outcomes. Interviews will be audio-recorded with participants' consent and transcribed verbatim for analysis.

**iii) Data Analysis Techniques**

Qualitative data analysis will involve thematic analysis to identify recurring patterns, themes, and conceptual categories within the interview transcripts. A systematic coding process will be employed to categorize and organize the data, guided by the conceptual framework and research questions. Emerging themes will be further analyzed and interpreted to provide nuanced insights into the mechanisms through which BI influences DM and OE in UI administration.

**iv) Integration of Quantitative and Qualitative Findings**

The quantitative and qualitative data along with triangulation enhance the rigor and depth of research. It allows for a comprehensive exploration of the research phenomenon and the results obtained from different data sources and methods. The integrated findings will be synthesized to develop a coherent narrative that addresses the research objectives and contributes to theoretical advancement and practical implications in the field of BI and UI administration.

## 4. Results and Interpretation

### 4.1 Measurement model

i) Demographics

Age, The majority of respondents fall within the 25-34 age group (20 individuals), constituting 100% of that age category. Other age groups are also represented, with varying numbers of participants. Gender, among the respondents, 56% identify as male, while 44% identify as female. Educational Background, The highest proportion of participants (29 individuals) hold a bachelor's degree, accounting for 100% of that category. Other educational levels (master's and doctoral degrees) are also represented. Occupational Status The majority (22 individuals) is employed, representing 100% of that group. Other categories include self-employed, unemployed, and retired individuals. Experience in UI, Most respondents (24 individuals) have worked in UI for less than 1 year, constituting 100% of that group. Other experience levels (1-2 years, 3-5 years, etc.) are also present. Organization Size, the largest group (25 individuals) works in organizations with 1-10 employees, representing 100% of that category. Role within the Organization, Executive/managerial roles are held by 21 participants (100% of that group). Other roles (supervisor/team leader, administrative/support staff, IT/technical staff) are also represented. The data provides near into the demographics and characteristics of the respondents.

**Table 1.** Demographic Profile

| Name | Preference | N | | Percentage | |
|---|---|---|---|---|---|
| Age | 25-34 | 20 | 100 | 20 | 100 |
| | 35-44 | 22 | | 22 | |
| | 45-54 | 14 | | 14 | |
| | 55-64 | 26 | | 26 | |
| | 65 years old or over | 18 | | 18 | |
| Gender | Male | 56 | 100 | 56 | 100 |
| | Female | 44 | | 44 | |
| Education | Bachelor's degree | 29 | 100 | 29 | 100 |
| | Master's degree | 33 | | 33 | |
| | Doctoral Degree | 38 | | 38 | |
| Occupation | Employed | 22 | 100 | 22 | 100 |
| | Self-employed | 22 | | 22 | |
| | Unemployed | 30 | | 30 | |
| | Retired | 26 | | 26 | |
| Worked in the UI | Less than 1 year | 24 | 100 | 24 | 100 |
| | 1-2 years | 23 | | 23 | |
| | 3-5 years | 20 | | 20 | |
| | 6-10 years | 15 | | 15 | |
| | More than 10 years | 18 | | 18 | |
| | 1-10 employees | 25 | 100 | 25 | 100 |

| | | | | | |
|---|---|---|---|---|---|
| Size of the organization | 11-50 employees | 20 | | 20 | |
| | 51-200 employees | 17 | | 17 | |
| | 201-500 employees | 19 | | 19 | |
| | More than 500 employees | 19 | | 19 | |
| Role within the organization | Executive/Managerial | 21 | 100 | 21 | 100 |
| | Supervisor/Team Leader | 16 | | 16 | |
| | Administrative/Support Staff | 18 | | 18 | |
| | IT/Technical Staff | 22 | | 22 | |

**ii) Descriptive analysis**

Mean this represents the average value of the variable for each group. For example, the mean BI score is 3.484. Minimum the smallest value observed in each group. For instance, the minimum OE score is 1.2.Maximum the largest value observed in each group. The maximum UI score is 4.86. Standard deviation This measures the variability or spread of the data. A smaller SD indicates less variability around the mean. Kurtosis describes the shape of the distribution. Positive kurtosis (0.518 for BI) indicates a more peaked distribution. Skewness indicates the asymmetry of the distribution. Positive skewness (0.872 for BI) means the following is longer on the right. "N" The sample size for each group is 100 in our case.

**Table 2.** Descriptive test

| | Mean | min | max | SD | kurtosis | Skewness | N |
|---|---|---|---|---|---|---|---|
| BI | 3.484 | 1.8 | 5.0 | .6297 | 0.518 | .872 | 100 |
| OE | 3.186 | 1.2 | 4.74 | .7601 | 0. 388 | .648 | 100 |
| UI | 3.444 | 1.4 | 4.86 | .6153 | 0. 472 | .743 | 100 |
| DM | 3.186 | 1.2 | 5.00 | .7047 | 0.280 | .526 | 100 |

**iii) Measurement Validation**

Table 3 provided outer loadings, Cronbach's alpha values, CR, and AVE for different factors. Outer Loadings play a crucial role in validating measurement models and their corresponding latent factors. Higher loadings indicate stronger associations in the "BI" factor, BI 1 has a loading of 0.766, BI 2 has 0.761, and so on. Cronbach's alpha assesses the internal consistency reliability of a scale or construct. It measures how well the items within a factor correlate with each other. The values identified (0.809, 0.751, 0.806, and 0.907) indicate good reliability. Higher values are desirable. CR is another measure of internal consistency, similar to Cronbach's alpha. It assesses the reliability of the factor by considering both the loadings should ideally be above 0.7 for reliable constructs. AVE quantifies the proportion of variance captured by the latent factor relative to measurement. The AVE values (0.560, 0.524, 0.676, and 0.725) should ideally exceed 0.5 for valid constructs. Overall, it seems your measurement model demonstrates good reliability and validity.

**Table 3**: Scales measurement validation.

| Factors | Indicators | Outer loadings | Cronbach Alpha values | CR | AVE |
|---|---|---|---|---|---|
| **BI** | | | **0.804** | **0.809** | **0.560** |
| | BI 1 | 0.766 | | | |
| | BI 2 | 0. 761 | | | |
| | BI 3 | 0.757 | | | |
| | BI 4 | 0.758 | | | |
| | BI 5 | 0.698 | | | |
| **DM** | | | **0.670** | **0.751** | **0.524** |
| | DM 1 | 0.826 | | | |
| | DM 2 | 0.786 | | | |
| | DM 3 | 0.828 | | | |
| | DM 4 | 0.710 | | | |
| | DM 5 | 0.720 | | | |
| **OE** | | | **0.748** | **0.806** | **0.676** |
| | OE 1 | 0.706 | | | |
| | OE 2 | 0.735 | | | |
| | OE 3 | 0.709 | | | |
| | OE 4 | 0.810 | | | |
| | OE 5 | 0.862 | | | |
| **UI** | | | **0.905** | **0.907** | **0.725** |
| | UI 1 | 0.827 | | | |
| | UI 2 | 0.820 | | | |
| | UI 3 | 0.874 | | | |
| | UI 4 | 0.833 | | | |
| | UI 5 | 0.900 | | | |

**iv) Discriminant validity Test**

Table 4 appears to be a discriminant validity test using the heterotrait-monotrait (HTMT) ratio. The values in the table represent the HTMT ratios among pairs of constructs. These ratios assess whether the constructs are distinct from each other (i.e., they have discriminant validity). The HTMT ratio for the "DM" and "BI" constructs is 0.882. The HTMT ratio for the "OE" and "BI" constructs is 0.404. Again, this value indicates discriminant validity. The HTMT ratio for the "UI" and "BI" constructs is 0.436, which also supports discriminant validity. Average Variance Extracted (AVE) Coefficients these coefficients exceeded 0.5, which indicates strong convergent validity for your theoretical model. In other words, the constructs in your model are closely related and measure the same underlying concept. Discriminant Validity Assessment shown in Table 4 by examining the Heterotrait-Monotrait Ratio (HTMT) values below 0.850, you've ensured minimal multicollinearity issues among the constructs. This means that the constructs are distinct and not highly correlated with each other.

**Table 4.** Discriminant validity test - HTMT ratio

| | **BI** | **DM** | **OE** | **UI** |
|---|---|---|---|---|
| **BI** | | | | |
| **DM** | 0.882 | | | |
| **OE** | 0.404 | 0.886 | | |
| **UI** | 0.436 | 0.490 | 0.686 | |

The Fornell-Larcker standard evaluates the discriminant validity within a structural equation framework (SEM). It specifically examined if the square root of the mean variance extracted (AVE) for each construct exceeds the inter-construct correlations. A higher AVE than the correlations implies distinctiveness invalidity. The principal values 0.749 for BI, 0.723 for DM, etc., denote the AVE for each construct, reflecting the variance portion clarified by the indicators of the construct. Non-principal values signify inter-construct correlations, 0.715 between BI and DM, 0.400 between DM and OE. To confirm distinctiveness in validity, one should contrast the square root of the AVE (principal values) with the correlations (non-principal values). When the square root of the AVE exceeds the correlation, it affirms distinctiveness invalidity. For instance, the AVE for BI (0.749) improves on its correlation with DM (0.715), endorsing distinctiveness between these constructs. Conversely, the AVE for DM (0.723) falls below its correlation with OE (0.400), prompting concerns regarding their distinctiveness invalidity.

**Table 5.** Discriminant validity test - Fornell-Larcker criterion

| | **BI** | **DM** | **OE** | **UI** |
|---|---|---|---|---|
| **BI** | 0.749 | | | |
| **DM** | 0.715 | 0.723 | | |
| **OE** | 0.777 | 0.400 | 0.822 | |
| **UI** | 0.786 | 0.787 | 0.695 | 0.851 |

Table 6 represents the correlation coefficients between different factors BI, DM, OE, and UI. BI and DM there is a positive correlation between BI and DM. When organizations leverage BI effectively, it enhances DM capabilities. BI and OE, BI positively impacts OE. As BI adoption increases, OE improves, leading to better overall performance. BI and UI, BI significantly influences UI. When UIs utilize BI tools, they enhance their interface design and functionality. DM and OE, DM correlates positively with OE. Effective decisions contribute to better organizational outcomes.OE and UI, OE directly affects UI. High OE translates to well-designed and efficient interfaces. In summary, BI serves as a strategic resource, positively impacting DM, OE, and UI. Organizations that harness BI effectively can attain sustainable competitive advantage and superior performance.

**Table 6.** Cross loadings

| | BI | DM | OE | UI |
|---|---|---|---|---|
| **BI 1** | **0.766** | 0.670 | 0.624 | 0.549 |
| **BI 2** | **0. 761** | 0.623 | 0.531 | 0.675 |
| **BI 3** | **0.757** | 0.493 | 0.825 | 0.495 |
| **BI 4** | **0.758** | 0.659 | 0.613 | 0.668 |
| **BI 5** | **0.698** | 0.894 | 0.465 | 0.612 |
| **DM 1** | 0.742 | **0.826** | 0.585 | 0.778 |
| **DM 2** | 0.705 | **0.786** | 0.786 | 0.630 |
| **DM 3** | 0.660 | **0.828** | 0.494 | 0.877 |
| **DM 4** | 0.685 | **0.710** | 0.755 | 0.532 |
| **DM 5** | 0.613 | **0.720** | 0.525 | 0.692 |
| **OE 1** | 0.621 | 0.632 | **0.706** | 0.591 |
| **OE 2** | 0.734 | 0.795 | **0.735** | 0.831 |
| **OE 3** | 0.858 | 0.622 | **0.709** | 0.735 |
| **OE 4** | 0.794 | 0.797 | **0.810** | 0.744 |
| **OE 5** | 0.558 | 0.849 | **0.862** | 0.696 |
| **UI 1** | 0.618 | 0.553 | 0.558 | **0.827** |
| **UI 2** | 0.732 | 0.749 | 0.709 | **0.820** |
| **UI 3** | 0.797 | 0.631 | 0.605 | **0.874** |
| **UI 4** | 0.844 | 0.787 | 0.714 | **0.833** |
| **UI 5** | 0.596 | 0.580 | 0.582 | **0.900** |

v) Regression Analysis

R-Square represents the proportion of variance in the dependent variable BI, that can be explained by the independent variables (UI, DM, OE). An R-Square of 0.293 means that approximately 29.3% of the variability in BI can be accounted for by these predictors. This metric adjusts R-Square for the number of predictors in the model and the sample size. An adjusted R-squared of 0.271 considers model complexity, providing a more accurate assessment of the model's explanatory power. Standard Error of the Estimate This reflects the average distance between observed values and the regression line. Essentially, it quantifies the standard deviation of prediction errors. A smaller value indicates a better fit of the model to the data.

Change Statistics This indicates the change in R-Square due to adding or removing predictors from the model. The F Change value 13.274 tests whether the predictors significantly improve the model. Durbin-Watson tests for autocorrelation in the residuals. ANOVA Test Table 8 Regression Sum of Squares Measures the variance explained by the predictors UI, DM, and OE. It is 8.143. The residual Sum of Squares represents the unexplained variance after accounting for the predictors. It is 19.631. Total Sum of Squares The total variance in the dependent variable BI. It is 27.774.F-Statistic Tests whether the regression model significantly explains the variance in BI. The F value 13.274 is highly significant ($p < 0.001$). The regression model, including UI, DM, and OE as predictors, significantly explains the variance in BI. However, the adjusted R Square suggests that the model might not explain as much variance as desired. Further analysis could involve examining individual predictor coefficients, assessing collinearity, and considering additional variables.

**Table 7.** Regression Analysis

**Model Summary[b]**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate | Change Statistics | | | | | Durbin-Watson |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | R Square Change | F Change | df1 | df2 | Sig. F Change | |
| 1 | .541[a] | .293 | .271 | .4522 | .293 | 13.274 | 3 | 96 | <.001 | 1.243 |

a. Predictors: (Constant), UI, DM, OE

b. Dependent Variable: BI

**Table 8.** Regression analysis- ANOVA test

**ANOVA[a]**

| Model | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| 1 | Regression | 8.143 | 3 | 2.714 | 13.274 | <.001[b] |
| | Residual | 19.631 | 96 | .204 | | |
| | Total | 27.774 | 99 | | | |

a. Dependent Variable: BI

c. Predictors: (Constant), UI, DM, OE

vi) One-way ANOVA

One-way ANOVA is a statistical method that evaluates whether there's a significant difference in group means, indicating at least one group differs from the rest. The Sum of Squares measures the total variation within and across these groups. Degrees of Freedom (df) represent the number of independent values that are free to vary during the analysis. The Mean Square is the average of these squared deviations, adjusted for df, essentially reflecting variance. The F-statistic is used to determine if the variability among group means exceeds what could be expected by chance. Lastly, the Sig. (p-value) indicates the probability that the observed data would occur under the null hypothesis, providing a measure of statistical significance. In summary, one-way ANOVA helps us determine if there are significant differences in crop yields (or any other dependent variable) among the different manures.

**Table 9.** One-way ANOVA test

| **ANOVA** |
|---|

| | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| **DM** | Between Groups | 7.719 | 12 | .643 | 3.197 | <.001 |
| | Within Groups | 17.502 | 87 | .201 | | |
| | Total | 25.220 | 99 | | | |
| **OE** | Between Groups | 4.146 | 12 | .646 | 2.117 | <.001 |
| | Within Groups | 26.914 | 87 | .309 | | |
| | Total | 31.060 | 99 | | | |
| **UI** | Between Groups | 8.547 | 12 | .712 | 2.141 | <. 001 |
| | Within Groups | 28.940 | 87 | .333 | | |
| | Total | 37.486 | 99 | | | |

4.2 Structural Model

i) Modeling

In our investigation, we utilize the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach via Smart PLS 4.0 software. Our objective is to construct and scrutinize a framework derived from previous scholarly work. This scrutiny encompasses the examination of path coefficients, levels of significance, and the determination coefficient ($R^2$) pertinent to each dependent variable. We meticulously observe the directionality and statistical significance of the path coefficients, employing a bootstrapping method with 5000 iterations to confirm the consistency of our findings. The path coefficients are instrumental in elucidating the magnitude and trajectory of the interrelations among the variables. Within our research framework, a positive path coefficient denotes a direct correlation between constructs, whereas a negative coefficient indicates an inverse correlation. The size of the coefficient denotes the intensity or degree of this correlation. For determining statistical significance, we depend on the corresponding t-values. The bootstrapping method involving 5000 iterations is employed to derive these t-values, confirming the solidity of our conclusions. $R^2$ measures the proportion of variance in the dependent variables (response variables) that a model explains. Higher $R^2$ values indicate that the model effectively captures the variations in the dependent variables based on the independent variables. It serves as an indicator of model fit. The Combined Model $R^2$ refers to the overall integrity of fit for the entire model. It considers all the predictors collectively. A higher combined $R^2$ suggests that the model provides a better explanation for the observed data. Individual $R^2$ Values Analyzing $R^2$ for each variable separately helps understand how well each predictor contributes to explaining the variance in the dependent variable. Increased individual $R^2$ values indicate stronger relationships between specific predictors and the outcome. Figure 2 visually represents the structural model used to test hypotheses. It outlines the relationships among latent constructs (factors) and their observed indicators (variables). SEM techniques are commonly employed to validate such models.

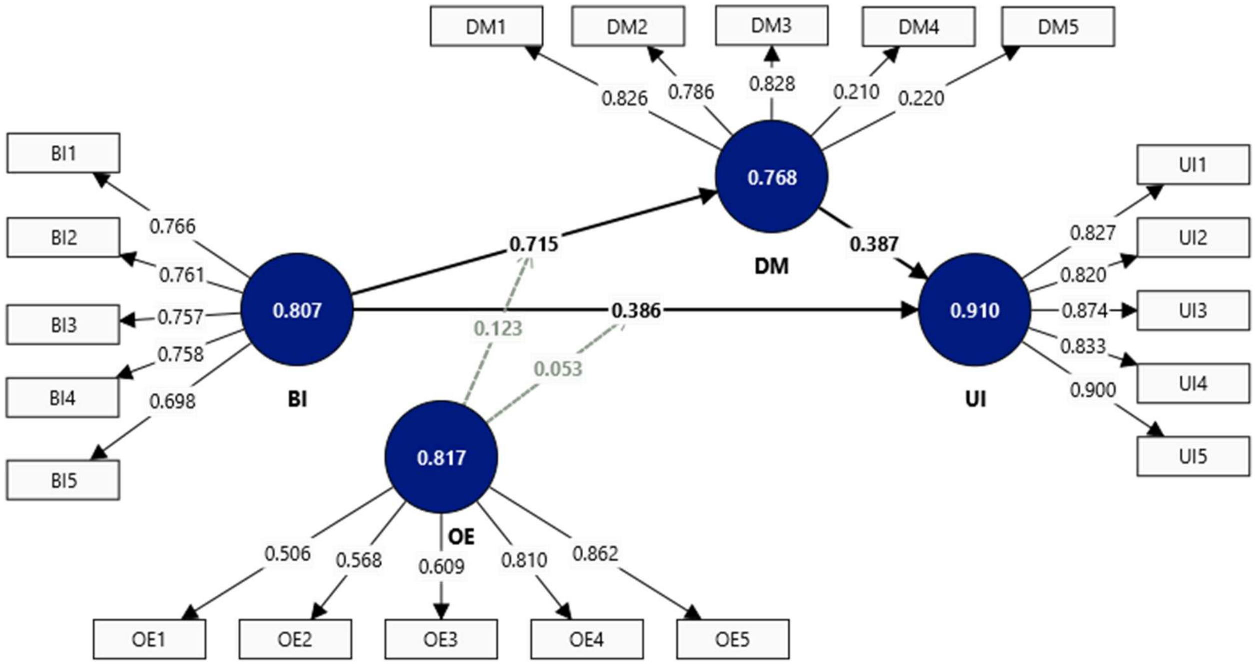


**Figure 2** Structural Model

**ii) Hypothesis testing**

In this section, we delve into the outcomes of hypothesis testing using Smart PLS 4.0 software. Partial Least Squares Structural Equation Modeling (PLS-SEM) is a favored approach for exploratory research aimed at theory-building. Its robust framework enables the analysis of intricate models and relationships. The component-based nature of PLS-SEM proves advantageous when dealing with hierarchical structures, especially in studies involving multiple constructs and items—precisely the case in our research. We deliberately chose PLS-SEM as our analytical tool to explore the interactions among BI, OE, UI, and DM. Notably; PLS-SEM's non-parametric characteristics alleviate the strict normal distribution assumptions typically required by other methods. This flexibility allows us to analyze data without imposing stringent constraints. Through bootstrapping, which estimates standard errors and assesses the significance of parameter estimates, we gained a comprehensive understanding of the relationships investigated. For detailed path coefficients and their corresponding p-values, refer to Table 10.

**Table 10.** Path coefficient Test

| Path | β | Standard deviation (STDEV) | T statistics | P values |
|---|---|---|---|---|
| BI -> DM | 0.652 | 0.225 | 2.896 | 0.004 |
| BI -> UI | 0.211 | 0.078 | 2.714 | 0.007 |
| DM-> UI | 0.613 | 0.257 | 2.713 | 0.003 |
| OE -> DM | 0.639 | 0.241 | 2.568 | 0.000 |
| OE -> UI | 0.605 | 0.083 | 2.798 | 0.000 |

a) Mediator test

BI -> DM -> UI The path represents the sequence of variables β of 0.023 indicating that a one-unit increase in BI is associated with a 0.023-unit increase in DM, which in turn leads to a similar increase in UI. The t-statistic 2.418 is greater than the critical t-value indicating statistical significance. The p-value of 0.006 is less than 0.05, suggesting that this path is statistically significant. The confidence interval (2.50% to 97.50%) provides a range within which we can be 95% confident that the true effect lies. OE -> DM -> UI. The β of 0.018 suggests that a one-unit increase in OE leads to a 0.018-unit increase in DM, which subsequently affects UI. The t-statistic (2.133) is also significant. The p-value (0.016) is less than 0.05, indicating statistical significance. Both paths show significant relationships between BI, OE, UI, and DM.

**Table 11**: Mediation effect test

| Path | β | STDEV | T statistics | P values | 2.50% | 97.50% |
|---|---|---|---|---|---|---|
| BI -> DM -> UI | 0.023 | 0.035 | 2.418 | 0.006 | 0.229 | 0.624 |
| OE -> DM -> UI | 0.018 | 0.008 | 2.133 | 0.016 | 0.054 | 0.638 |

b) Moderator test

The beta coefficient of 0.144 indicates that a one-unit increase in the interaction between OE and BI corresponds to a 0.144-unit increase in the dependent variable DM. The t-value of 2.749 exceeds the critical t-value, indicating statistical significance. Additionally, the p-value of 0.012 is less than 0.05, confirming the significant interaction effect. Similarly, for the interaction OE x BI -> UI, the beta coefficient (0.085) suggests that a one-unit increase in the OE-BI interaction leads to a 0.085-unit increase in UI. The t-value of 2.417 is also greater than the critical t-value, and the p-value of 0.008 is less than 0.05, signifying statistical significance. Both OE x BI -> DM and OE x BI -> UI are statistically significant. However, further analysis is needed to understand the practical implications and direction of these effects.

**Table 12.** Moderating effect test

| Path | β | STDEV | T value | P value |
|---|---|---|---|---|
| OE x BI ->DM | 0.144 | 0.059 | 2.749 | 0.012 |
| OE x BI ->UI | 0.085 | 0.035 | 2.417 | 0.008 |

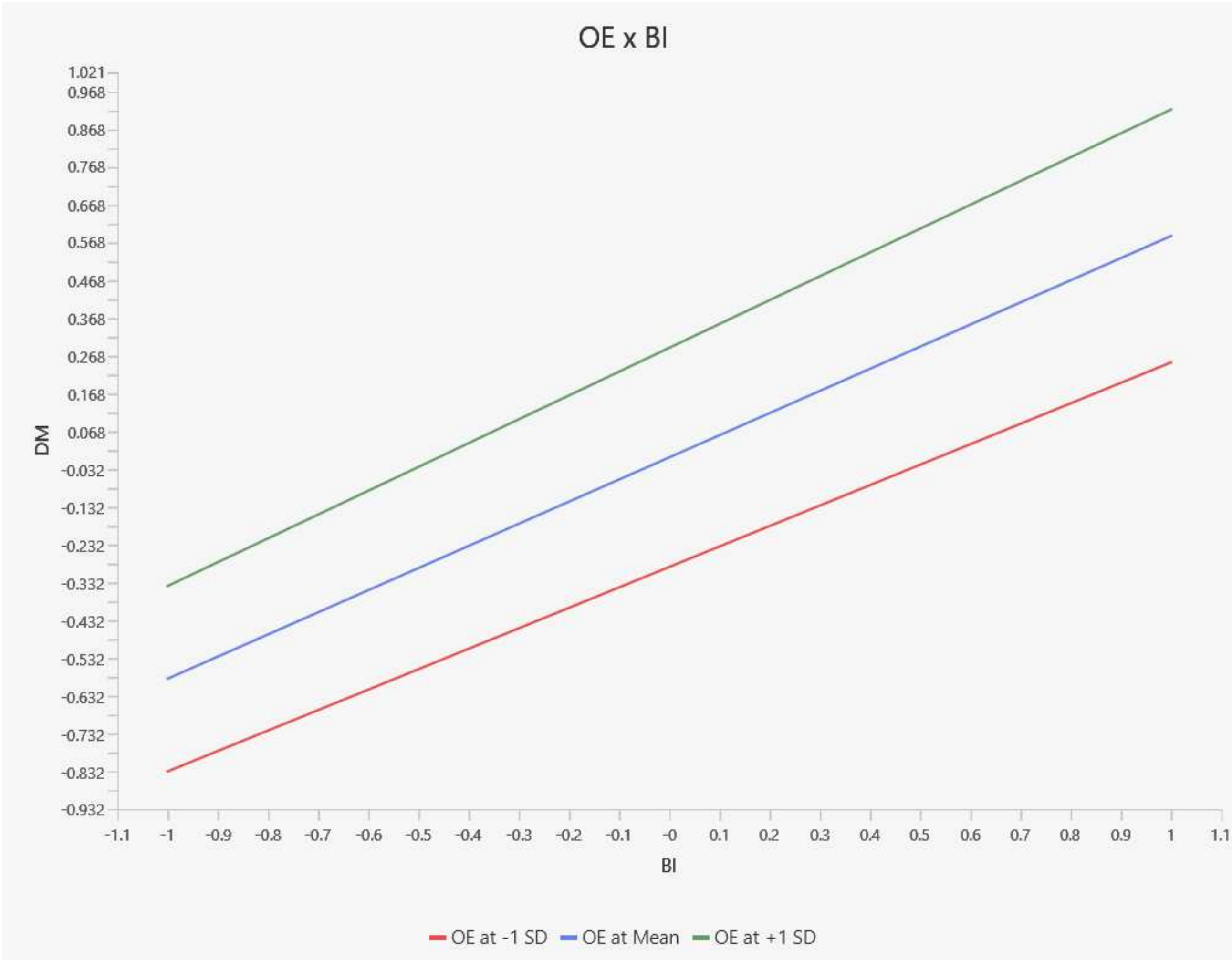


**Figure-3 Moderating test**

**5. Discussion:**

In today's era of data-driven operations, BI tools play a crucial role in shaping corporate strategies and boosting competitive advantages. This research delves into BI's transformative impact on UI systems, with a specific focus on DM and OE and their interconnectedness. BI acts as a robust assurance mechanism. By integrating predictive analytics, BI enhances branch efficiency through the automation of previously manual processes [36]. Enhanced data management also allows teams to redirect their efforts toward core business activities. The promise of BI lies in its capacity to make organizations more agile and responsive, enabling them to seize new opportunities and foster innovation in highly competitive markets [37]. Moreover, BI empowers enterprises to efficiently analyze and leverage vast and diverse datasets with precision. In the banking sector, integrating disparate systems through BI eliminates the need for manually preparing individual reports for each system. By harnessing BI within UI, banks can gather extensive consumer data, thereby enhancing client service capabilities [38]. BI also provides deeper insights into consumer behavior, enabling banks to proactively address issues before they escalate. Additionally, BI streamlines data management by directly interfacing with core system databases, eliminating the complexities of manual data handling [38, 39]. Implementing a comprehensive BI solution across the organization empowers DM to make data-driven decisions, reducing reliance on guesswork and bolstering competitive advantages [39][23]. Confirming Hypothesis 1, findings indicate a positive correlation between BI and UI. BI tools facilitate insights into UI data, thereby enabling informed DM and resource allocation, as evidenced by a standardized path coefficient of 0.386. Hypothesis 2 explores the positive relationship between BI and DM. BI empowers DM through real-time analytics, aiding in policy formulation and resource allocation, with a standardized path coefficient of 0.715. Hypothesis 3 examines the positive correlation between DM and UI, with a coefficient of 0.387. Hypothesis 4 indicates DM's role as a mediator in the positive relationship between BI and UI, with a coefficient of 0.023. BI enhances DM processes, indirectly influencing UI outcomes. According to Hypothesis 6, OE moderates the positive relationship between BI and DM. Efficient processes amplify BI's impact on DM effectiveness. Furthermore, OE moderates the positive relationship between BI and UI, enhancing UI program delivery and responsiveness through streamlined operations. BI's evolution from a support tool to a strategic asset underscores its critical role in UI systems. BI tools, particularly when integrated with AI, IoT, and ML, enhance DM efficiency and adaptability to changing environments. Challenges such as the demand for skilled personnel highlight the necessity for dynamic BI approaches aligned with market trends and technological advancements. In summary, BI represents more than just a tool; it catalyzes enhancing DM, and OE, and ultimately, improving UI outcomes. Organizations must embrace this paradigm shift to fully leverage BI's transformative potential in the UI domain [5]. This study's insights hold practical implications for UI, advocating for BI adoption to enhance DM effectiveness and secure competitive advantages. It provides a distinctive viewpoint and empirical evidence on the benefits of BI utilization, offering practical insights for UI enhancements [23].

**Conclusion:**

This research aims to investigate the influence of BI on OE and perceived profitability within UI. Analyzing 100 responses, the study uncovers a positive and statistically significant relationship between BI and OE. This finding is consistent with prior research. [40], [42], [43], and [44], which have similarly conceptualized BI in this manner. Moreover, the research demonstrates that BI notably enhances the profitability of banks. From a theoretical perspective, this finding contributes to RBV theory, which posits that an organization's unique and valuable resources lead to competitive advantage and superior performance. In the context of UI, BI can be regarded as a strategic resource. By implementing BI, UIs can enhance their OE, thereby positively affecting profitability. Additionally, the study suggests that BI implementation fosters the development of organizational capabilities within banks, ultimately emphasizing BI's strategic role as a resource that contributes to sustainable competitive advantage and long-term success. It represents a valuable addition to RBV theory, highlighting BI's critical importance as a strategic asset for banks. Despite its contributions, the study acknowledges certain limitations. Future research could explore the nuanced mechanisms through which different facets of BI impact UI. Specifically, examining the effects of specific BI components. Furthermore, investigating the effects of specific BI techniques on OE and profitability could provide valuable insights [79]. Additionally, exploring contextual factors and IT infrastructure that influence BI effectiveness within UI would enhance our understanding [23].

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