IRAQI STATISTICIANS JOURNAL

https://isj.edu.iq/index.php/isj

ISSN: 3007-1658 (Online)

Diagnose Insomnia by using Fuzzy Multiple Ordinal Logistic Regression

Bashar Khalid Ali[1], Sackineh Shamil Jasim[2]

[1,2]Department of Statistics, Administration and Economics College, Kerbala University- Kerbala –Iraq

ARTICLE INFO

Article history:

Received 9 January 2026
Revised 9 January 2026
Accepted 31 March 2026
Available online 3 April 2026

Keywords:

Insomnia
Crisp set
Fuzzy set
Granular fuzzy set
Ordinal logistic regression

ABSTRACT

This research utilized a questionnaire designed to diagnose and analyze insomnia using the ordinal logistic regression model. The model was applied to traditional, fuzzy, and granular fuzzy data. Two hundred questionnaires were distributed across five locations, or "granules": the College of Nursing (40 questionnaires), the College of Administration and Economics (45 questionnaires), the College of Science (40 questionnaires), the College of Education (35 questionnaires), and the Middle Euphrates Department (35 questionnaires). The target audience included professors, staff, and male and female students from various age groups. The study concluded that the ordinal logistic regression model for a granular fuzzy sample was more accurate than using traditional and fuzzy data. Analysis of the phenomenon of insomnia revealed that it has physical and psychological effects, manifesting as fatigue, headaches, and poor concentration due to unhealthy habits such as excessive caffeine consumption, irregular sleep patterns, and excessive use of electronic devices.

1. Introduction

Insomnia is a common sleep disorder that impacts daily life and overall health. It is characterized by several symptoms, including difficulty falling asleep, and may be strongly linked to certain diseases such as heart disease and weakened immunity. Insomnia can range from severe to moderate to mild, which necessitates an ordinal classification and the use of a model capable of handling such data. Furthermore, there can be inaccuracies in diagnosing this condition, requiring the use of fuzzy logic to obtain accurate predictions. Through this integrated approach, the research seeks to improve the accuracy of medical assessment and diagnosis of insomnia and provide a practical and effective tool for clinicians and medical researchers to analyse insomnia data and gain a more comprehensive understanding of its dynamics. Many researchers have addressed the topic of fuzziness and ordinal logistic regression. The first to introduce fuzzy set theory were the Azerbaijani researcher Lotfi Zadah and the German D. Klaua in 1965, as an extension of traditional sets. A fuzzy set is a set of elements in which each element has a degree of belonging between zero and one. This set explains the ambiguity and became a solution to the problem of imprecision [16, 24]. They were followed by many research studies that addressed logistic regression, fuzzy data, and fuzzy granular samples. In 2011, Das and Rahman used ordinal logistic regression analysis to identify risk factors for child malnutrition in Bangladesh, aiming to pinpoint the causes of malnutrition instead of applying the traditional binary logistic regression model [10]. In 2014, Tian Chen et al. used ordinal

Corresponding author E-mail address: bashar.k@uokerbala.edu.iq
https://doi.org/10.62933/azx8wg44

logistic regression for data with outliers instead of traditional linear regression, where the data follow a normal distribution [20]. In 2015, Pedrycz et al. used granular fuzzy models to model discrete data, instead of traditional models [23]. In 2019, Al-Fatlawi used ordinal logistic regression to identify the most important factors affecting household income, collecting data from 384 individuals in the Karbala Governorate [2]. In 2021, Al-Khairullah and Al-Bhldawi) used Bayesian methods to estimate the parameters of ordinal logistic regression models using the Markov Chain Monte-Carlo algorithm [8]. In 2022, Salim et al. used fuzzy least squares to predict the likelihood of developing type 2 diabetes using conventional and fuzzy logistic regression to study type 2 diabetes patients [3]. In the same year (2022), Lelisho et al. used ordinal logistic regression to determine the effect of independent variables on the socioeconomic status of families in Tebeya, south-western Ethiopia [18]. In 2023, Diao et al. used fuzzy granular logistic regression to classify individual prosthetic hand gestures based on electromyography using prosthetic systems to improve the quality of life of patients after amputation and proposed a fuzzy granular logistic regression algorithm [21]. In the same year (2023), researchers Gamez-Granados et al. predicted student performance in distance learning courses using artificial intelligence algorithms and proposed using an improved ordinal classification algorithm based on ordinal logistic regression to predict student performance in four classification categories (withdrawn, failed, passed, and excellent) [15]. In 2024, researchers Moawed et al. and Sherif A. used ordinal logistic regression to classify and predict milk production in cows into low, medium, and high categories [19]. Also in 2024, researchers Mitani et al. applied survey weights to ordinal logistic regression models to improve inference in samples based on ordinal results, relying on survey-weighted ordinal logistic regression models with weights inversely proportional to sample fractions [9]. It is noteworthy that researchers have used logistic regression techniques in previous studies and research. For traditional and granular data, fuzzy logic and granularity were not combined in the context of multiple ordinal logistic regression, but in our research, multiple ordinal logistic regression was used for traditional fuzzy, fuzzy, and granular fuzzy data

2. Multiple Binary Logistic Regression:

The multiple binary logistic regression models are a common model for predicting the probability of an event by fitting data and information onto a logistic curve. This involves the relationship between a set of independent variables and a dependent variable, which can be categorical or ordinal. The model estimates the probability of an event occurring and can be simple with a single independent variable or multiple with several independent variables. [7] Multiple binary logistic regression is a nonlinear regression model and one of the most commonly used methods for analysing dichotomous data when the dependent variable is of the nominal type and follows a Bernoulli distribution with a probability of success (p). The dependent variable takes only two values: $\mathrm{Y}=1$ with a probability of success (p) and $\mathrm{Y}=0$ with a probability of failure $(1-\mathrm{p})$. Its purpose is to estimate the probability (P) of outcome (1) (such as injury, success, or acceptance) based on several independent variables $\{X_1, X_2, \dots, X_k\}$, j=1,2,…,k . [13][26[

The formula for the probability mass function of the Bernoulli distribution is as follows:

$\mathrm{P_r}(Y_i/X_i) = p^{y_i}\ (1-p)^{1-y_i}$ (1)

Where dependent variable with a two-response relationship : the probability of the response (success) occurring at $Y_i = 1$, $1-p_i$ the probability of the response (failure) not occurring at $Y_i = 0$.

Therefore, the prediction of the variable Y_i the probability of the response p_i occurring, where,

$E(Y_i) = p_r(Y = 1) = p_i$ (2)

The variance of the variable Y_i as follows:

$Var(Y_i) = p_i(1 - p_i)$ (3)

Therefore, the formula for the binary logistic regression model is as follows:

$Y_i = p_i + e_i$ (4)

Where p_i the multiple logistic regression function, it can be found using the following formula:

$$P_j = \frac{e^{\beta_0 + \sum_{j=1}^{k} \beta_j X_j}}{1 + e^{\beta_0 + \sum_{j=1}^{k} \beta_j X_j}} \quad (5)$$

Where β_0 the constant term of the model, ، β_j the coefficients of the independent variables (slope), X_j the independent variable j, e_j the random error term with a normal distribution with a mean $E(e_j) = 0$ and a constant variance $Var(e_j) = \sigma^2$, i.e. $e_j \sim N(0, \sigma^2)$, the number of parameters must be less than the sample size, i.e $1 + K < n$, n is the sample size, k is the number of independent variables.

Using the logit function, the model is as follows:

$$Log\left(\frac{p_j}{1-p_j}\right) = \beta_0 + \sum_{j=1}^{k} \beta_j X_j + e_j \quad (6)$$

3. Multiple Ordinals Logistic Regression

This is a type of logistic regression used when the dependent variable (response) is ordinal in nature, meaning it consists of categories Ordinaled in ascending or descending Ordinal (such as disagree, neutral, agree), and the aim is to study the effect of several independent variables on it. This type of analysis is used in cases where equal spacing between categories cannot be assumed, as in surveys and the fields of social, health, and psychological sciences. It aims to estimate the probability of individuals belonging to a particular category or less based on a set of independent variables. MORL is characterized by its ability to handle non-linear data and Ordinaled categories without the need to convert them into numerical variables. It also assumes the parallel lines assumption between levels of the dependent variable. It is widely used in analyzing survey data, satisfaction assessment studies, consumer behavior, education, and public health, as it can be used to identify the factors influencing the rise or fall of the response level. [2][11]

3.1Ordinal Logistic Regression Assumptions

Every statistical method has certain assumptions, meaning that the data must meet specific conditions for the results of the statistical method to be accurate [19]. Regarding ordinal logistic regression, its assumptions are as follows:

1. Ordinarily: The categories of the dependent variable must be arranged in a logical or normal Ordinal (e.g., rating satisfaction: unsatisfied – neutral – satisfied).
2. Proportional Odds Assumption: Also known as the Parallel Lines Assumption, this means that the effect of the independent variables on the probability of transitioning from one category to another is the same across all category boundaries. That is, the regression coefficient for each independent variable is the same across all categories, but the cut-points differ.
3. No Multicollinearity: There should not be a very strong relationship between the independent variables to avoid conflicting estimates.
4. Independence of Observations: Each observation must be independent of the others; that is, each row in the data represents a distinct case unaffected by the others.
5. Linearity with Log Odds: The relationship between the continuous independent variables and log odds must be linear (but not with the dependent variable itself).

3.2 The Mathematical Model of Multiple Ordinal Logistic Regression

The relationship analysis can be represented when the dependent variable is ordinal and influenced by independent variables using the basic model of multiple ordinal logistic regression and a link function, as follows: [14[

In the following multiple linear regression model:

$$Y_j = \beta_0 + \sum_{j=1}^{k} \beta_j X_j + e_j \quad (7)$$

The relationship between the quantitative dependent variable (a continuous numerical value) Y_j and the set of independent variables is linear. The goal is to predict the value of the quantitative dependent variable as a result of the influence of the set of independent variables. However, in the Multiple Ordinal Logistic Regression (MORL) model, we use a logistic transformation of the same equation to estimate the probability of a specific event occurring when the relationship between the dependent (classificatory) variable is non-linear. This model is based on the Cumulative Logistic Regression (CLR) model, which is the most common form. It is used to estimate the probability that the dependent variable Y will be less than or equal to a specific class, compared to other higher classes, as follows:

$$\text{Log}_e\left(\frac{F(Y\leq j)}{1-F(Y\leq j)}\right) = \text{Log}_e(Odds) = \alpha_j - \sum_{j=1}^{k} \beta_j X_j + \varepsilon_j \quad (8)$$

Equation (8) is called the relative likelihood model using the Logit function because it is based on the assumption that the effects (trend) resulting from the independent variables $\underline{X}=(X_1, X_2, \ldots, X_i)$ are the same for all classes on a logarithmic scale. It is also called the relative likelihood model assuming parallel lines, as it depends on the cumulative probabilities of the response classes.

Where Log_e The natural logarithm of the base e, used to convert a ratio to a linear scale. $F(Y\leq j)$ The cumulative probability (probability of success) that the response will be in the class j or less than or equal to Y. . $1 - F(Y\leq j)$ The probability of failure, which is the probability that the value will be greater than y. That is:

$$Odds\ (Y) = \text{Ln}\left(\frac{Secsess\ Probability}{failure\ \ Probability}\right) \quad (9)$$

Odds(Y) represents the probability ratio between the probability of success and the probability of failure; that is, the probability ratio of the dependent variable y being less than or equal to class j versus being greater than j. j is the number of alternatives. α_j the cutoff constant associated with each class j of the dependent variable, such that each class has a different value for α_j . $\sum_{j=1}^{k} \beta_j X_j$ sum of the products of the coefficients β_j and the independent variables X_j, that representing the effect of the independent variables on the probability of belonging to the class or less. ε_j is the random error or residuals, which in some formulas is not explicitly written because it is assumed to be built into the logistic distribution.

The reason for taking the natural logarithm of the quantity $\frac{F}{1-F}$ is that we want to convert the probability p (which is always between 0 and 1) into an unbounded quantity that takes values between ∞ and -∞ so that it can be modelled by a linear relationship such as regression, as follows:

$$\frac{F(Y\leq j)}{1-F(Y\leq j)} = e^{\alpha_j - \sum_{j=1}^{K} \beta_j X_j}$$

$$\frac{F(Y\leq j)}{1-F(Y\leq j)} = \frac{e^{\alpha_j - \sum_{j=1}^{K} \beta_j X_j}}{1+e^{\alpha_j - \sum_{j=1}^{K} \beta_j X_j}}$$

$$\big(1 - F(Y\leq j)\big) e^{\alpha_j - \sum_{j=1}^{K} \beta_j X_j} = F(Y\leq j)\left(1 + e^{\alpha_j - \sum_{j=1}^{K} \beta_j X_j}\right)$$

$$e^{\alpha_j - \sum_{j=1}^{K} \beta_j X_j} = F(Y\leq j) + F(Y\leq j) e^{\alpha_j - \sum_{j=1}^{K} \beta_j X_j} = F(Y\leq j)\left(1 + e^{\alpha_j - \sum_{j=1}^{K} \beta_j X_j}\right)$$

$$\therefore\ F(Y\leq j) = \frac{e^{\alpha_j - \sum_{j=1}^{K} \beta_j X_j}}{\left(1+e^{\alpha_j - \sum_{j=1}^{K} \beta_j X_j}\right)} \quad (10)$$

When we want to find the probability of a specific category, it is as follows:

$$F(Y = j) = F(Y\leq j) - F(Y\leq j-1) \quad (11)$$

And,

$$\text{Log}_e\left(\frac{F(Y\leq j)}{1-F(Y\leq j)}\right) = \text{Log}_e\left(\frac{1}{1+e^{\alpha_j - \sum_{j=1}^{K} \beta_j X_j}}\right) e^{\alpha_j - \sum_{j=1}^{K} \beta_j X_j} \quad (12)$$

In other words, as x increases, β_j determines how $\text{Log}_e(Odds)$, i.e., the probability of the event, changes. This means we are relating a change in an independent variable to a change in the probability of the event, but in a non-linear way because probability does not grow linearly.

Returning to the multiple ordinal logistic regression equation (8), and assuming we have the following alternatives:

Strongly agree	agree	neutral	Disagree	Strongly disagree
Number of alternatives (categories) j=5				

In ordinal logistic regression, the number of equations must be equal to (the number of alternatives - 1). If we have five alternatives, we have four equations. If we have two alternatives, we have one equation, which is the equation for binary logistic regression (whether there is one independent variable or several independent variables). In the case of five alternatives, the four equations are as follows:

$$p(Y \leq j = \text{Strongly disagree}) = p(1) \quad (13)$$

$$p(Y \leq j = \text{Disagree}) = p(1) + p(2) \quad (14)$$

$$p(Y \leq j = \text{neutral}) = p(1) + p(2) + p(3) \quad (15)$$

$$p(Y \leq j = \text{agree}) = p(1) + p(2) + p(3) + p(4) \quad (16)$$

There is no need to extract $p(Y \leq j = \text{Strongly agree})$ since we are finding a cumulative probability, and the result of this probability equals one, so there is no need to extract it. Therefore, we have four rates for five alternatives (j = 1, 2, 3, 4, and 5), meaning that:

$$p(Y \leq j = \text{Strongly agree}) = \mathrm{p}(1) + \mathrm{p}(2) + \mathrm{p}(3) + \mathrm{p}(4) + \mathrm{p}(5) = 1 \quad (17)$$

We will have the equations for multiple ordinal logistic regression as follows:

$$\mathrm{Log_e}(\mathrm{p}(\mathrm{Y} \leq \mathrm{j} = \text{Strongly disagree})) = \alpha_1 - \sum_{j=1}^{K} \beta_j X_j + \varepsilon_j \quad (18)$$

$$\mathrm{Log_e}(\mathrm{p}(\mathrm{Y} \leq \mathrm{j} = \text{Disagree})) = \alpha_2 - \sum_{j=1}^{K} \beta_j X_j + \varepsilon_j \quad (19)$$

$$\mathrm{Log_e}(\mathrm{p}(\mathrm{Y} \leq \mathrm{j} = \text{neutral})) = \alpha_3 - \sum_{j=1}^{K} \beta_j X_j + \varepsilon_j \quad (20)$$

$$\mathrm{Log_e}(\mathrm{p}(\mathrm{Y} \leq \mathrm{j} = \text{agree})) = \alpha_4 - \sum_{j=1}^{K} \beta_j X_j + \varepsilon_j \quad (21)$$

We observe from equations (18) to (21) that the values of the regression slope coefficients are the same in each of the four equations because their weights do not differ across the classes. This is a condition of ordinal logistic regression, namely the parallel lines assumption, as it relies on the cumulative probabilities of the response classes. However, the equations differ only in the value of α_j. This assumption means that the effect of each independent variable, X_j, on the dependent variable is constant across all Ordinated classes. That is, a change in X_j has the same effect on the transition from (strongly disagree) to (disagree), from (disagree) to (neutral), from (neutral) to (agree), or from (agree) to (strongly agree)

2.3 Model estimation

The cumulative logistic model, which is the default model for ordinal logistic regression, is expressed by equation (9). Then a probability is formulated, and from this, the parameters of the ordinal logistic regression model are estimated using the Maximum Likelihood Estimation (MLE) method, regardless of the number of independent variables. By applying equation (10), it can be expressed as shown below: [4]

Each category has a response as follows:

$$\frac{e^{\alpha_j - \sum_{j=1}^{K} \beta_j X_j}}{1+e^{\alpha_j - \sum_{j=1}^{K} \beta_j X_j}} - \frac{e^{\alpha_{j-1} - \sum_{j=1}^{K} \beta_j X_j}}{1+e^{\alpha_{j-1} - \sum_{j=1}^{K} \beta_j X_j}} \quad (22)$$

$$p_j(Y_j) =$$

$$L = \prod_{i=1}^{n} \prod_{j=1}^{J} [p_j(Y_j)]^{y_{ij}} \quad (23)$$

$$= \prod_{i=1}^{n} \prod_{j=1}^{J} \left[\frac{e^{\alpha_j - \sum_{j=1}^{K} \beta_j X_j}}{1+e^{\alpha_j - \sum_{j=1}^{K} \beta_j X_j}} - \frac{e^{\alpha_{j-1} - \sum_{j=1}^{K} \beta_j X_j}}{1+e^{\alpha_{j-1} - \sum_{j=1}^{K} \beta_j X_j}} \right]^{y_{ij}} \quad (24)$$

The Maximum Likelihood Estimation (MLE) method relies on maximizing the logarithm of the likelihood function. The logarithm of the likelihood function reflects the possibility or probability of predicting the observed values of the response variable using the independent variables: [4]

The logarithm of likelihood is expressed

$$\log L = \sum_{i=1}^{n} \sum_{j=1}^{J} Y_{ij} . \log \left[\frac{e^{\alpha_j - \sum_{j=1}^{K} \beta_j X_j}}{1+e^{\alpha_j - \sum_{j=1}^{K} \beta_j X_j}} - \frac{e^{\alpha_{j-1} - \sum_{j=1}^{K} \beta_j X_j}}{1+e^{\alpha_{j-1} - \sum_{j=1}^{K} \beta_j X_j}} \right] \quad (25)$$

By deriving equation (25) for the coefficients to be estimated and using a numerical iterative method, the results are obtained. In this research, we have relied on the ready-made program (SPSS) to find the parameter estimates.

4. Fuzziness and Fuzzy Logic

In 1965, Lutfi Zadeh, an Azerbaijani-born professor of mathematics, electronics engineering, and software engineering at the University of California, Berkeley, laid the foundations for Fuzzy Sets theory. Fuzzy logic has been used in some expert systems and artificial intelligence applications. In our real world, we encounter many sets, categories, or classifications where elements are categorized according to a characteristic or criterion that is not clearly defined. It's difficult to determine the extent or degree to which an element belongs to a particular category or set. Fuzziness represents a lack of clarity, or more broadly, ambiguity in describing things. Many phenomena do not have definitively established boundaries, such as long, much more, small,… etc. They are somewhat true and somewhat false. We can call these terms fuzzy concepts. These are concepts that the human brain works with, but computers do not. Fuzziness has become a solution to problems that... It suffers from inaccuracy in its measurements [6.[

Let $\mathbf{\Omega}$ be a universal set. The sub-fuzzy set $\tilde{A}$ of $\mathbf{\Omega}$, characterized by the membership function$\mu_{\tilde{\mathbf{A}}}(\mathbf{x})$ which produces values between [0,1] for all x values in the fuzzy sample space, is the fuzzy set of Ordinated pairs: [22][25]

$$\tilde{A} = \left\{ \left(x_i, \mu_{\tilde{A}}(x_i)\right), x \in \Omega, i = 1,2,3, \dots \dots n, 0 \le \mu_{\tilde{A}}(x) \le 1 \right\} \quad (26)$$

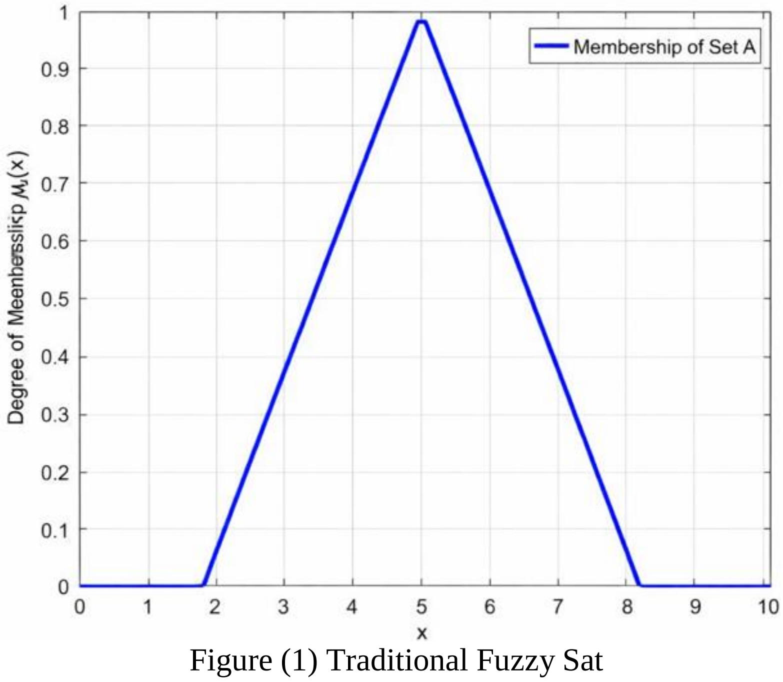

Figure (1) Traditional Fuzzy Sat

Figure 1 illustrates the representation of a traditional fuzzy set, which is an extension of a classical set by allowing for varying degrees of membership for elements instead of being limited to absolute membership or no membership at all. Membership functions are used to represent these degrees, enabling the expression of imprecise or uncertain knowledge in a mathematically flexible manner. This representation is a cornerstone of fuzzy logic and its various applications, particularly in intelligent decision-making systems and the analysis of human behaviour.

4.1 Membership Functions

The membership function is an important function in fuzzy set theory. It can be expressed as the function that generates the values of the elements belonging to the fuzzy set that fall within the range of real numbers on the closed interval [0,1]. It can be expressed in several ways: either numerically, as a vector representing the membership range of the fuzzy set, or functionally, which relies on factorization to construct a function that determines the degree of membership for each element. Membership functions take various forms and are considered important parameters. [12[

4.2 Granular Fuzzy Set

This is an advanced extension of traditional fuzzy set theory, used to represent knowledge or data more accurately and flexibly by dealing with small units of information called granules. These granules are subsets of data that share similar characteristics and are grouped together to form a fuzzy granule with a specific degree of belonging. [27] In a traditional fuzzy set, each element has a single degree of belonging to the set. In a granular fuzzy set, however, an element may belong to an information granule a subset with similar characteristics and this granule itself belongs to a larger set to a certain degree. This reduces complexity when dealing with large or unclear datasets and mimics the way humans think about dealing with ambiguous or imprecise concepts. This type of set is used in decision-making systems, classification, machine learning, medicine, and engineering. [28]

If we have a set X divided into fuzzy sets i at different granular levels j as follows:

$$X = \bigcup_{i=1}^{n} A_i^j \qquad (27)$$

Where i is for the subgroup within a given granularity level, and j is for the granularity level.

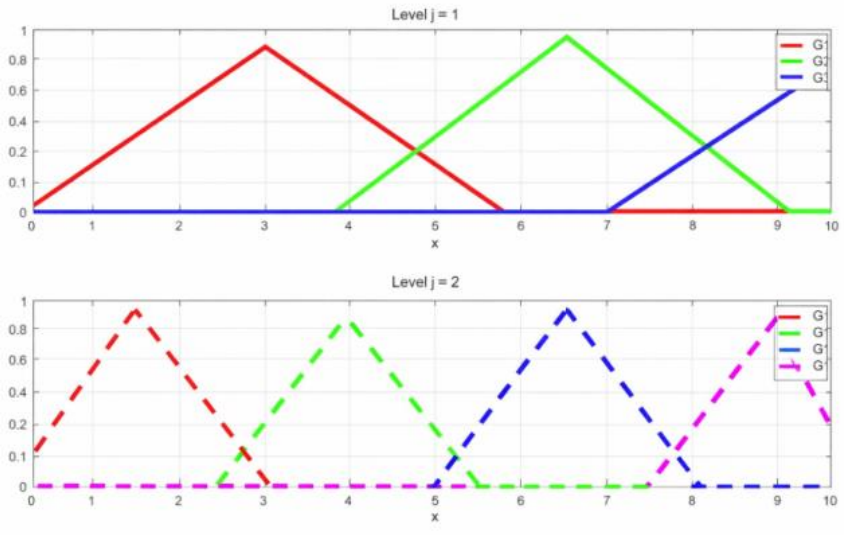

Figure (2) Granular fuzzy sample

Figure 2 illustrates a visual representation of a two-level fuzzy granular structure. The first granular level (j=1) represents a division of the data into three fuzzy subsets (G_1^1, G_2^1, and G_3^1), representing general categories covering the entire range from 0 to 10, using nested triangular membership functions that reflect the gradual nature of membership. The second granular level (j=2) shows a more detailed division of the same range into four fuzzy granules (G_1^2, G_2^2, G_3^2, and G_4^2), with each function narrowing its range and increasing the degree of membership.

4. Real Data set:

A questionnaire was prepared to collect information about the phenomenon under study. It was distributed at the University of Karbala in four colleges: (College of Nursing, College of Administration and Economics, College of Science, College of Education), as well as in the Middle Euphrates Department. The target group was (faculty members, employees, and students) of both genders, in different age groups and according to (marital status, academic qualification, and monthly income). It included seven sections: Section 1 (Demographic Data), Section 2 (Lifestyle and Daily Habits), Section 3 (Assessment of Insomnia), Section 4 (Factors Affecting Insomnia), Section 5 (Psychological and Physical Factors), and Section 6 (Assessment of Insomnia Based on the Five-Point Likert Scale). It was distributed and collected by way of (direct interviews) from the research sample consisting of (200) individuals (Appendix A). The data consisted of (40) forms in the College of Nursing, (45) forms in the College of Administration and Economics, (40) forms in the College of Science, (40) forms in the College of Education, and (35) forms in the Middle Euphrates Department. These were distributed on January 29, 2025. The data were analysed using MATLAB 2023b, Excel, and SPSS VER23, and were described as follows: Y represents the dependent variable (severity of insomnia), which has ordinal levels (Y_1: mild insomnia, Y_2: moderate insomnia, Y_3: severe insomnia). X_1 represents the independent variable (symptoms of insomnia). X_2 represents the independent variable (environmental factors affecting sleep). X_3 represents the independent variable (daily habits and their effect on insomnia). X_4 represents the independent variable (psychological and health impact of insomnia).

5. Reliability Test

To test the quality of the research scale, Cronbach's Alpha test and Guttman's Lambda test were used to measure the reliability of the scale results. Table (1) shows the value of Cronbach's Alpha and Guttman's Lambda coefficients:

Table (1) Research Test

Cronbach's Alpha	Number of questions	
.90	63	
Guttman's Lambda		
Lambda	1	.886
	2	.912
	3	.893
	4	.916
	5	.896
Sum	63	

Table (1) shows that the Cronbach's alpha coefficient for the questionnaire used in the study (consisting of 63 questions) is very high, reaching (0.90). This indicates a high degree of internal consistency among the instrument's items, meaning that the questions measure the same dimension or concept consistently and systematically. According to established statistical standards, a Cronbach's alpha value exceeding 0.9 is considered excellent and indicates that the instrument is highly reliable in measuring the phenomenon under study, thus enhancing the credibility of the results obtained from this questionnaire. We also note that most Guttman's Lambda coefficients range between 0.886 and 0.916, indicating that the questionnaire or test has very good internal reliability. These values are an indication that the questions, in general, measure the same concept or dimension consistently. The validity of the research scale was also tested by presenting it to a group of (5) expert reviewers specializing in psychological, medical and statistical sciences to determine the extent to which the items are suitable for measuring what they were prepared for, the extent to which the answer alternatives are appropriate, to identify the items that need modification, and to present the proposed modification, after the experts and specialists expressed their opinions, observations and modifications to some of the scale items.

6. Data Analysis:

6 1.Demographic Analysis of the Research Sample:

Table (2) shows the distribution of the research sample according to (gender, marital status, age, educational qualification, monthly income) as follows:

Table (2) Demographic distribution of the research sample

Variable	Class	Frequancy	Relative frequency
Sex	ذكر	104	52
	أنثى	96	48
	Sum	**200**	**100**
Marital Status	married	138	69
	single	54	27
	divorcee	8	4
	widow	0	0
	Sum	**200**	**100**
Age	Less than 30	54	27
	(35-30)	32	16
	(40-36)	48	24
	(45-41)	22	11
	(50-46)	22	11
	50 and more	22	11
	Sum	**200**	**100**
Qualification	PHD	46	23
	Msc.	30	15
	Bechelor	106	53
	Other	18	9
	qualification	**200**	**100**
monthly income	Below average	14	7
	middle	88	44
	Above average	74	37
	high	24	12
	Sum	**200**	**100**

Table (2-3) shows the distribution of the sample members according to the demographic distribution. We note that males formed the majority with a number of (104) and a percentage of (52%), while females numbered (96) and a percentage of (48%), which indicates a relative balance between the sexes. In terms of marital status, most of the people were married (138, or 69%), followed by single people (54, or 27%), and divorced people (8, or 4%). There were no widows in the sample (0, or 0%), which shows that the family structure was mostly stable. In terms of age categories, the most common were those under 30 (54, or 27%), followed by people aged 36 to 40 (48, or 24%), and then people aged 30 to 35 (32, or 16%). There were 22 people (11%) in each of the three age groups: 41–45, 46–50, and above 50. This shows a good range of ages. The largest group of people had a bachelor's degree (106, or 100%). The second largest group had a PhD (46, or 23%), and the third largest group had a Master's degree (30, or 15%). This shows that the sample was quite educated. Most of the people who answered (88 or 44%) said their monthly income was average, while the next most common answer (74, or 37%) said their income was above average. Only a tiny percentage (14, or 7%) said their income was below average, which suggests that the sample's economy is doing well

6.2 analysis of Life style, habits:

Table (3) Sample members according to daily life and habits

Variable	Class	Frequancy	Relative frequency
Do you engage in any physical activity regularly?	Yes	96	48
	No	104	52
	Sum	**200**	**100**
How many hours of work or study per day?	Less than 4 hours	24	12
	6-4hours	54	27
	8-6hours	82	41
	More than 8 hours	40	20
	Sum	**200**	**100**
How many hours do you spend in front of screens?	Less than an hour	40	20
(Television, telephone, computer) daily?	3-1hours	104	52
	6-3hours	28	14
	More than 6 hours	28	14
	Sum	**200**	**100**
Do you consume beverages containing caffeine (coffee, tea, energy drinks)?	Yes	168	84
	No	32	16
	Sum	**200**	**100**
Do you smoke?	Yes	32	16
	No	168	84
	Sum	**200**	**100**

Table (3-3) indicates that the majority of the sample (104, or 52%) do not engage in regular physical activity, while less than half (96, or 48%) reported engaging in regular physical activity. This indicates a comparatively low level of interest in physical exercise within the group. The biggest group (82, or 41%) works or studies 6 to 8 hours a day. The second biggest group (54, or 27%) works 4 to 6 hours a day, the third biggest group (24, or 12%) works less than 4 hours a day, and the smallest group (40, or 20%) works or studies more than 8 hours a day. This shows that most of the people in the sample spend a lot of time working or studying. Over half of the participants (104, or 52%) said they spent 1 to 3 hours a day on screens (TV, phone, or computer). The next most common answer was less than an hour (40, or 20%). The groups that spent 3–6 hours and more than 6 hours had the same size (28, or 14%), which shows that screen use was not very common in the sample. In terms of caffeine intake, the results indicated that most of the sample (168, or 84%) drank caffeinated drinks, while just 32 (or 16%) did not. This shows that these drinks were common among the participants. Finally, 168 of the 168 people in the sample (84%) did not smoke, whereas 32 people (16%) smoked. This shows that smoking is not very common in this group.

6.3 Insomnia Assessment Analysis:

The table below shows the distribution of the sample members regarding the number of hours of sleep, its quality, the problems they face, the prevalence of insomnia among them, and their use of sleep medications.

Table (4) Distribution of Sample Members According to Their Assessment of Insomnia

Variable	Class	Frequancy	Relative frequency
How many hours of sleep do you get per day on average?	Less than 4 hours	14	7
	6-4hours	86	43
	8-6hours	84	42
	More than 8 hours	16	8
	Sum	**200**	**100**
How would you describe the quality of your sleep?	Excellent	12	6
	Good	98	49
	Medium	76	38
	weak	14	7
	Sum	**200**	**100**
Are you suffering from:	Difficulty falling asleep (starting to sleep(	46	23
	Difficulty staying asleep	40	20
	Wake up early	84	42
	uncomfortable sleep	30	15
	Sum	**200**	**100**
If you suffer from insomnia, how long has it been since you started suffering from it?	Less than a month	90	45
	From one month to six months	22	11
	From 6 months to 1 year	38	19
	More than a year	50	25
	Sum	**200**	**100**
Do you use any sleep medications?	Yes	12	6
	No	188	94
	Sum	**200**	**100**

Table (4) indicates that the largest percentage of individuals sleep between 4 and 6 hours daily, totaling (86) and representing (43%), followed by those who sleep between 6 and 8 hours, totaling (84) and representing (42%). The lowest percentages were those who sleep less than 4 hours, totaling (14) and representing (7%), and those who sleep more than 8 hours, totaling (16) and representing (8%). This suggests that most of the sample does not get enough sleep according to scientific standards. Most of the participants (98, or 49%) said their sleep was good. The next most common answer was average (76, or 38%), and the last was poor (14, or 7%). Only a few people (12, or 6%) said their sleep was great, which shows that most people don't think their sleep quality is good. The most prevalent kind of insomnia reported by the participants was waking up early in the morning (84, or 42%). This was followed by trouble going asleep (46, or 23%), trouble remaining asleep (40, or 20%), and lastly, restless sleep (30, or 15%). This shows that the people in the sample had different types of sleep disturbances. An analysis of the duration of insomnia showed that the largest group (90, or 45%) had been suffering for less than a month, while 25% (50) had been suffering for more than a year. The rest of the percentages were as follows: 38 (19%) had been suffering for 6 months to a year and 22 (11%) had been suffering for 1 to 6 months. This shows that a large number of people have chronic insomnia. The majority of the sample reported not using sleeping pills, with 188 individuals (94%) abstaining, in contrast to a minority of 12 individuals (6%) who did use them. This may indicate the participants' inclination to eschew pharmacological intervention or a lack of awareness regarding suitable treatments for insomnia.

Table (5) Names of the most commonly drungs

Drug Name	Frequancy	Relative frequency
)Metformin(	2	1
)Pantoprazole(	2	1
) Prazosin(	2	1
Non	194	97
Sum	**200**	**100**

Table (5) demonstrates that 97% of people (194) do not frequently use any medicine. This shows that most people in the sample do not need on going medical care. This might be because they are generally healthy or because they don't want to go to the doctor. Conversely, only a small number of participants reported using medications: metformin (2, or 1%), pantoprazole (2, or 1%), and prazosin (2, or 1%). This indicates a minimal degree of pharmaceutical dependency among the group. These findings also indicate that the use of drugs associated with chronic or psychological illnesses, such as diabetes, gastrointestinal problems, or stress-induced hypertension, remains constrained within the examined cohort.

6.4 Analysis of factors affecting insomnia:

Table (6) Factors Affecting Insomnia

Variable	Class	Frequency	Relative frequency
Do you suffer from daily stress or psychological pressure?	Yes	200	100
	No	0	0
	Sum	**200**	**100**
If the answer is yes, what are the sources of stress?	the job	58	29
	the study	24	12
	Family problems	48	24
	Financial situation	4	2
	Other reasons	66	33
	Sum	**200**	**100**
Do you have any chronic health problems that affect your sleep?	Yes	42	21
	No	158	79
	Sum	**200**	**100**
Have you noticed any effect on your sleep due to:	Lifestyle changes (such as travel, night work(	62	31
	Eating a heavy meal before bedtime	26	13
	noise	80	40
	Room temperature	24	12
	Other reasons	8	4
	Sum	**200**	**100**

Table (6) shows that all (200) members of the research sample (100%) suffer from daily stress or psychological pressure, indicating a very high prevalence of stress in the studied sample and the absence of any individual who does not experience stress. This shows that the environment is full with pressures, both at work and in social situations. The most prevalent cause of stress was "other," which was chosen by (66) people (33%). This suggests that there were many elements, whether personal or psychological, that weren't listed in the alternatives. After that, work-related stress was mentioned by 58 people (29%), and family concerns were mentioned by 48 people (24%). Only 24 people (12%) said that the study itself stressed them out, and only 2 people (4%) said that their money problems stressed them out the most. This suggests that social and professional factors are the primary determinants of the sample's mental health. In terms of chronic health issues, 42 people (21%) have chronic illnesses that influence their sleep, whereas 79% (158 people) do not. This shows that a large number of people are badly affected by sleep in terms of their mental and physical health. Noise was the most common source of sleep problems; with 40% (80 people) saying it was the main reason. Next came changes in lifestyle, such working or travelling at night (31%, 62 people), then eating big meals before bed (13%, 26 people), and finally room temperature (12%, 24 people). Lastly, 4% (8 people) of the variables were other things. This shows that sleep may be impacted by a number of environmental and behavioural factors that people can control and improve by being aware of them and making adjustments to their lives.

Table (7) Distribution of chronic health problems suffered by patients

chronic health problems	**Frequency**	**Relative frequency**
Pressure and pain in the neck and joints	2	1
High blood pressure	10	8
Sinusitis	2	1
Bronchial asthma	2	1
Diabetic	4	2
Pressure & Diabetic	2	1
Chronic migraine	4	2
Colon	2	1
Joints	10	5
Bronchial sensitivity	2	1
Stomach ulcers and migraines	2	1
Non	158	79
Sum	**200**	**100**

Table (7) indicates that the vast majority of the sample (158, or 79%) do not suffer from any chronic health problems, suggesting that most participants enjoy good general health. The remaining percentage was distributed among a range of chronic health problems, most notably joint problems (10, or 5%), followed by hypertension (10, or 8%), then migraine and diabetes (4 each, or 2%). The remaining problems were distributed at relatively low percentages of 1% each (2 individuals), including neck and joint pain, sinusitis, bronchial asthma, irritable bowel syndrome, diabetes with hypertension, bronchial sensitivity, and peptic ulcer associated with migraine. It is noteworthy that diseases of the nervous, muscular, and cardiovascular systems represent the largest proportion of chronic cases, although these are limited compared to the total sample size.

6.5 Analysis of psychological and physical factors:

Table (8) Psychological and physical factors specific to the sample members

Variable	Classes	Frequency	Relative frequency
Are you experiencing symptoms of anxiety or depression؟	Yes	200	100
	No	0	0
	Sum	**200**	**100**
If the answer is yes, how much does it affect your sleep؟	weak effect	72	36
	Middle effect	82	41
	high effect	46	23
	Sum	**200**	**100**
Are you experiencing physical pain that affects your sleep؟	Yes	48	24
	No	152	76
	Sum	**200**	**100**
Have you ever been diagnosed with any psychological or neurological disOrdinals؟	Yes	22	11
	No	178	89
	Sum	**200**	**100**

Table (8) shows that the study results revealed that all participants (200, or 100%) suffered from symptoms of anxiety or depression. This shows that the sample has a lot of psychological issues and that there are a lot of them in the community being investigated. When asked how these psychological symptoms affected their sleep, the biggest group (82, or 41%) said it had a moderate influence, followed by a weak effect for 72 (36%), and a strong effect for 46 (23%). This indicates that psychological conditions influence sleep to differing extents, predominantly moderate or weak. About a quarter of the sample (48, or 24%) said they had physical pain that made it hard to sleep, while the majority (152, or 76%) did not. This indicates that the direct physical impact on sleep is relatively limited. Regarding previous diagnoses of psychological or neurological disorder, most participants reported not having experienced any such diagnosis, numbering (178) and representing (89%), while only a small number acknowledged having experienced a previous diagnosis, numbering (22) and representing (11%), which may indicate either limited access to psychological care or a lack of self-awareness of the existence of clear psychological disorder.

Table (9) Distribution of sample members according to type of pain

Type of pain	Frequancy	Relative frequency
convulsions	2	1
Persistent itching and headaches	2	1
Lower back pain - herniated disc	2	1
Headache pain	14	7
Headache and eye pain	2	1
joint pain	10	5
Joint pain – feet	2	1
Joint pain and pressure	2	1
Joint and spinal pain	2	1
Joint pain and headache	2	1
Back pain	2	1
Non	158	79
Sum	**200**	**100**

Table (9) indicates that the vast majority of individuals (158, or 79%) do not suffer from any type of pain, suggesting that the overall physical condition of the sample is relatively stable. In contrast, the types of pain reported by the remaining participants varied. The most common was headache (14, or 7%), followed by joint pain (10, or 5%). The remaining types of pain appeared at equally low rates of 1% each (2 participants), and included cramps, persistent itching and headache, lower back pain due to a herniated disc, headache and eye pain, joint and foot pain, joint and pressure pain, joint and spinal pain, joint and headache pain, and back pain. These results reflect that the physical complaints in the sample are primarily concentrated in headaches and joint pain, which are among the most common types of pain in societies experiencing psychological stress or leading sedentary lifestyles.

Table (10) Distribution of sample members according to the type of psychological and neurological disorder

Type of psychological or neurological disOrdinals	Frequancy	Relative frequency
depression	6	3
Anxiety	10	5
Obsessive-compulsive disOrdinal	2	1
Non	182	91
Sum	**200**	**100**

Table (10) indicates that the majority of the sample (182, or 91%) do not suffer from any psychological or neurological disorder, suggesting low rates of diagnosis or reporting of these disorder within the sample. Conversely, a small percentage of participants were distributed across different types of disorder, the most common being anxiety disorder al (10, or 5%), followed by depression (6, or 3%), while obsessive-compulsive disorder appeared at a very low rate of 1% (2). These results indicate that the prevalence of diagnosed psychological disorder among the sample remains limited, which may be attributed to a lack of awareness or a failure to seek professional diagnosis, despite the presence of psychological symptoms, as other findings in the study have shown.

6.6 Estimating the Multiple Ordinal Logistic Regression Model for Traditional Data:

Before estimating the model, the assumptions of the Multiple Ordinal Logistic Regression model must be verified as follows:

6.6.1 Normality of Categories for Traditional Data:

This assumption requires that the categories of the dependent variable be disorder in a logical or normal Ordinal (ascending, descending, or a logical sequence). This is what the questionnaire (Section 6) showed, as the categories were disorder in a regular and logical normal Ordinal (never, rarely, sometimes, often, always), where each category represents a degree or level of frequency or intensity.

6.6.2 Proportional Odds Assumption for Traditional Data:

If the effect of independent variables on the probability of transitioning from one class to another is the same across all class boundaries (the slopes remain constant regardless of changes in the cut-off point between classes), then the general model can be compared to the null hypothesis model using the Log-2 likeness statistic and the chi-square test to verify this assumption, as shown in Table (11)

Table (11) Proportional Odds Assumption for Traditional Data

Model	-2 Log Likelihood	Chi-Square	Df	Sig.
Null Hypothesis	.000	-	-	-
General	1.000	.000	256	1.000

Table (11) indicates that the null hypothesis, which states that the location parameters (slope coefficients) are the same across response categories, is not rejected, and thus this assumption is fulfilled.

6.6.3 Lack of Multicollinearity among independent variables in traditional data:

To test this hypothesis, the variance inflation factor was used, as shown in Table (12).

Table (12) Testing the Multicollinearity problem in traditional data.

Model	Collinearity Statistics	
	Tolerance	VIF
X_1	.541	1.850
X_2	.672	1.488
X_3	.535	1.869
X_4	.436	2.292

Table (12) shows that the Variance Amplification Factor (VIF) indicates that the independent variables X_1, X_2, X_3, and X_4 do not exhibit Multicollinearity. The values show that all variables have a Tolerance greater than 0.1 and a VIF less than 10, which are the generally accepted thresholds for detecting Multicollinearity. Specifically, the Tolerance values range between 0.436 and 0.672, indicating that each variable retains a sufficient proportion of its own variance that is not shared by the other variables. Meanwhile, the VIF values range between 1.488 and 2.292, which are significantly lower than the critical threshold of 10 that typically indicates Multicollinearity. Therefore, it can be concluded that the model does not suffer from significant Multicollinearity, and the input variables can be used in the analysis without concern about noise resulting from high correlation between them.

6.6.4 Independence of Observations for Traditional Data:

To test this hypothesis, the Durbin-Watson test was used, as shown in Table (13), for traditional data.

Table (13) Durbin-Watson Test for Observational Independence on Traditional Data

Model	Durbin-Watson
1	1.674

he results of the (Durbin-Watson) test in Table (13) indicate that its value reached (1.674), which is close to the ideal value (2), indicating that there is no significant autocorrelation between the remnants of the model, and thus the condition of independence of the observations is met to an acceptable degree.

6.6.5 Linearity with log odds for traditional data

To test this hypothesis, the Box-Tidwell test was used, as shown in Table (14).

Table (14) Box-Tidwell test for traditional data

Box-Tidwell test		Sig.	Decision	Relation
Location	x_1	.561	Significant	Linear
	x_2	.261	Significant	Linear
	x_3	.221	Significant	Linear
	x_4	.123	Significant	Linear
	$x_1 \ln x_1$	0.189	Significant	Linear
	$x_2 \ln x_2$	0.489	Significant	Linear
	$x_3 \ln x_3$	0.289	Significant	Linear
	$x_4 \mathrm{Ln} x_4$	0.382	Significant	Linear

The Box-Tidwell test (Table 14) confirms the linearity hypothesis between the independent variables and the log odds in the ordinal logistic regression model. All probability values (Sig.) for the original variables x_1, x_2, x_3, and x_4, as well as for their interaction variables x1lnx1, $x_2 \ln x_2$, $x_3 \ln x_3$, and $x_4 \ln x_4$, exceeded the significance level of 0.01. This indicates that the relationship between these variables and the Logit of the dependent variable is statistically linear. Therefore, the model fulfils the linearity condition with log odds, and these variables can continue to be used within the logistic regression model without the need for transformation or reclassification.

6.6.6 Model Fit Test for Traditional Data

The -2 Log Likelihood and Chi-Square tests were used to extract fit information for the ordinal logistic regression model, as shown in Table (15).

Table (15) Model Fit Information for Traditional Data

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	1613.914		-	-
Final	.000	1613.914	4	.000

Table (15) shows that the estimated ordinal logistic regression model is highly significant. The value of (-2 Log Likelihood) for the Intercept Only model is (1613.914), representing the fit of the baseline model, which does not include any independent variables. This value drops to zero in the final model after the introduction of four independent variables, indicating a significant improvement in the model's fit to the data. The Chi-Square test shows that the improvement in model fit is (1613.914) with 4 degrees of freedom, at a significance level (Sig.) of 0.000, which is much less than 0.01. This indicates the rejection of the null hypothesis, which states that the independent variables have no effect. Therefore, it can be concluded that the model as a whole is statistically significant, and that the introduced variables contribute substantially to explaining the change in the dependent variable.

6.6.7 Model Fit Test for Traditional Real Data

The Chi-Square test was used to determine the fit of the ordinal logistic regression model to the real data, as shown in Table (16).

Table (16) Model Fit Test with Traditional Real Data

Statistic	Chi-Square	df	Sig.
Pearson	908.567	6756	.789
Deviance	890.117	6756	.778

Table (16) shows the results of the fit test for the ordinal logistic regression model with traditional real data. The model fits the real data well, as Pearson's chi-squared test yielded a value of (908.567) with (6756) degrees of freedom and a significance level (Sig.) of 0.789, which is greater than 0.01. This indicates no significant differences between the expected values provided by the model and the actual values, which is a positive indicator of the model's fit. The Skewness test also showed similar results, with a chi-squared value of (890.117) with the same degrees of freedom and a significance level of 0.778, also greater than 0.01. This reinforces the model's reliability and confirms that it explains the data well without significant statistical deviations. Therefore, it can be concluded that the model has good explanatory power and can be relied upon to analyse the relationship between the independent variables and the ordinal dependent variable with high statistical confidence.

6.6.8 Measuring the Explanatory Power of the Model for Traditional Data

The Cox and Snell, Nagelkerke, and McFadden tests were used to test the explanatory power of the model in explaining the variance in the dependent variable. This is known as the Pseudo-R-Square test, as shown in Table 17

Table 17: Results of the Pseudo-R-Square test for measuring the explanatory power of the model in explaining the variance in the dependent variable for traditional data.

Cox and Snell	1.000
Nagelkerke	1.000
McFadden	.994

Table (17) presents the results of the pseudo-R-squared measures, indicating that the multiple ordinal logistic regression models possess very high explanatory power. The Cox, Snell, and Nagelkerke values reached a maximum of 1.000, demonstrating that the model explains 100% of the variance in the dependent variable according to these two measures. The McFadden value reached 0.994, very close to 1, indicating excellent fit to the model. These values collectively reflect that the model achieves near-perfect agreement between the expected and actual values and demonstrates very strong predictive power, thus enhancing confidence in the model's validity and its use in explanation and prediction based on the input independent variables.

6.6.9 Estimating the Multiple Ordinal Logistic Regression Model for Traditional Data

Table (18) shows the estimated values of the coefficients under traditional data.

Table (18) Estimated Parameters under Ordinal Logistic Regression for Traditional Data

		Estimate	Std. Error	Df	Sig.
Threshold	[y = 1]	32.104	2.454	1	.000
	[y = 2]	46.919	3.042	1	.000
	[y = 3]	65.568	4.167	1	.000
	[y = 4]	80.853	5.181	1	.000
Location	x1	4.780	.363	1	.000
	x2	4.673	.350	1	.000
	x3	4.601	.388	1	.000
	x4	4.950	.389	1	.000

Table (18) shows the estimated parameters for multiple ordinal logistic regression of conventional data. All thresholds and location parameters are statistically significant and clearly contribute to predicting the dependent ordinal variable. Thresholds [y = 1] to [y = 4], representing the boundaries between classes of the dependent variable, all showed high statistical significance (Sig. = 0.000) with high estimation values. This indicates clear and distinct boundaries between classes, and that the model effectively distinguishes between different ranks of the dependent variable. As for the independent variables x_1, x_2, x_3, and x_4, they all have positive estimation values, meaning they have a positive effect on the probability of moving to a higher class of the dependent variable. All are also significant (Sig. = 0.000), demonstrating that their effect is not due to chance.

$$\text{Logit}\left(P(Y \leq K)\right) = \hat{\alpha}_j - \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \hat{\beta}_3 x_3 + \hat{\beta}_4 x_4 \quad ; j=1, 2, 3, 4 \qquad (28)$$

The four estimated equations for the four alternatives are as follows:

$$\text{Logit}\left(P(Y \leq 1)\right) = 32.104 - 4.780x_1 + 4.673x_2 + 4.601\ x_3 + 4.950\ x_4 \qquad (29)$$

$$\text{Logit}\left(P(Y \leq 2)\right) = 46.919 - 4.780x_1 + 4.673x_2 + 4.601\ x_3 + 4.950\ x_4 \qquad (30)$$

$$\text{Logit}\left(P(Y \leq 3)\right) = 65.568 - 4.780x_1 + 4.673\ x_2 + 4.601\ x_3 + 4.950\ x_4 \qquad (31)$$

$$\text{Logit}\left(P(Y \leq 4)\right) = 80.853 - 4.780x_1 + 4.673\ x_2 + 4.601x_3 + 4.950\ x_4 \qquad (32)$$

From equations (29) to (32), the following becomes clear:

1. In equation (29), the probability of an individual's insomnia being in the category of "never" or lower (the lowest category) is calculated. The high positive values of the coefficients associated with insomnia symptoms, environmental factors, daily habits, and psychological and health influences indicate that any increase in these factors reduces the probability of the individual remaining in the (never) category and pushes them towards higher categories of insomnia. This means that these factors contribute to the progression from not suffering from insomnia to its onset.
2. In equation (30), the probability of an individual's insomnia being (rare) or lower (i.e., (never) or (rare) is calculated. With the same independent variables having positive coefficients, this indicates that the more pronounced these factors become, the lower the probability of the individual remaining in the lower two categories and the higher the chances of moving to more severe categories of insomnia, such as (sometimes) or (more often) .
3. Equation (31), the Logit is the probability of the insomnia level being (sometimes) or lesser (i.e., never, rarely, or sometimes). With a high value for the constant and positive coefficients for the variables, it is clear that increasing these factors makes it more likely that the individual will move from intermediate to higher levels, such as "often," reflecting a gradual and clear increase in their impact.
4. In Equation (32), the Logit calculates the probability of the insomnia level being (often) or lesser (i.e., within any category except (always). With all coefficients being positive, the high values of the independent variables indicate a high probability of the individual moving to the highest category, (always). This means that these four factors are strongly and consistently associated with the deterioration of sleep and the development of persistent and severe insomnia in the individual.

Note that the fifth category, (always) represents the upper limit of the alternatives, and therefore does not need to be calculated because its probability is equal to one, as the probability is cumulative.

6.7 Estimating the Multiple Ordinal Logistic Regression Model for Fuzzy Data:

Before estimating the model, the assumptions of the multiple ordinal logistic regression model for fuzzy data must be verified as follows:

6.7.1 Normality of Classes for Fuzzy Data:

This assumption was confirmed using the questionnaire.

6.7.2 Proportional Odds Assumption for Fuzzy Data:

The Log-likelihood statistic and the Chi-Square test were used to determine the validity of this assumption, as shown in Table (19).

Table (19) Proportional Odds Assumption for Fuzzy Data

Model	-2 Log Likelihood	Chi-Square	Df	Sig.
Null Hypothesis	.000	-	-	-
General	1.000	.000	256	1.000

Table (19) indicates that the null hypothesis, which states that the location parameters (slope coefficients) are the same across response categories, is not rejected, and thus this hypothesis is verified.

6.7.3 No Multicollinearity in Fuzzy Data:

To test this hypothesis, the variance inflation factor was used, as shown in Table (20)

Table (20) Testing the Multicollinearity Problem in Fuzzy Data

Model	Collinearity Statistics	
	Tolerance	VIF
X_{1F}	.988	1.012
X_{2F}	.997	1.003
X_{3F}	.987	1.013
X_{4F}	.998	1.002

Table (20) shows that the independent variables X_1F, X_2F, X_3F, and X_4F do not exhibit multicollinearity, as all Tolerance values were greater than 0.1, ranging from 0.987 to 0.998. The Variance Amplification Factor (VIF) values were less than 10, ranging from 1.002 to 1.013, which is within statistically acceptable limits. These results indicate that each variable retains a significant portion of its variance, and there is no significant overlap between the independent variables.

6.7.4Independence of Observations for Fuzzy Data:

To test this hypothesis, the Durbin-Watson test was used, as shown in Table (21) for fuzzy data.

Table (21) Durbin-Watson Test

Model	Durbin-Watson
1	1.918

The results of the Durbin-Watson test, as shown in Table 21, indicate a value of 1.981, which is close to the ideal value of 2. This demonstrates the absence of significant autocorrelation between the residuals of the model, thus fulfilling the condition of observational independence to an acceptable degree.

6.7.5 Linearity with log odds for fuzzy data:

To test this hypothesis, the Box-Tidwell test was used, as shown in table 22.

Table 22: Box-Tidwell test for fuzzy data

Box-Tidwell test		Sig.	Decision	Relation
Location	x_{1F}	0.878	Significant	Linear
	x_{2F}	0.889	Significant	Linear
	x_{3F}	0.767	Significant	Linear
	x_{4F}	0.676	Significant	Linear
	$x_1 \ln x_{1F}$	0.665	Significant	Linear
	$x_{2F} \ln x_{2F}$	0.690	Significant	Linear
	$x_{3F} \ln x_{3F}$	0.889	Significant	Linear
	$x_{4F} L n x_{4F}$	0.789	Significant	Linear

The Box-Tidwell test in Table (22) confirmed the linearity hypothesis between the independent variables and the log odds in the ordinal logistic regression model for fuzzy data with a high degree of significance. All probability values (Sig.) for the parent variables x1F, x2F, x3F, and x4F, as well as for their interaction variables x_1Flnx$_1$F, x_2Flnx$_2$F, x_3Flnx$_3$F, and x_4Flnx$_4$F, were above the significance level of 0.01. This indicates that the relationship between these variables and the logit of the dependent variable is statistically linear. Therefore, the model satisfies the linearity condition with log odds, and these variables can continue to be used within the logistic regression model without the need for transformation or reclassification.

6.7.6 Model Fit Test for Fuzzy Data:

The -2 Log Likelihood and Chi-Square tests were used to extract the fit information for the ordinal logistic regression model for fuzzy data, as shown in Table (23).

Table (23) Model Fit Information for Fuzzy Data

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	469.082	-	-	-
Final	.000	469.082	4	.000

Table (23) shows that the estimated ordinal logistic regression model is highly significant. The value of (-2 Log Likelihood) for the Intercept Only model is (469.028), representing the fit of the baseline model, which does not include any independent variables. This value drops to zero in the final model after the introduction of four independent variables, indicating a significant improvement in the model's fit to the data. The chi-square test shows that the improvement in model fit is (469.028) with 4 degrees of freedom, at a significance level (Sig.) of 0.000, which is much less than 0.01. This indicates the rejection of the null hypothesis, which states that the independent variables have no effect. Therefore, it can be concluded that the model as a whole is statistically significant, and that the introduced variables contribute substantially to explaining the change in the dependent variable.

6.7.7 Model Fit Test for Fuzzy Real Data:

The Chi-Square test was used to determine the fit of the ordinal logistic regression model to the real data, as shown in Table (24).

Table (24) Model Fit Test for Fuzzy Real Data

	Chi-Square	df	Sig.
Pearson	1.644	696	0.989
Deviance	2.678	696	0.994

Table (24) shows the results of the fit test for the ordinal logistic regression model on fuzzy real data. The model fits the real data well, as Pearson's chi-squared test yielded a value of (1.644) with (696) degrees of freedom and a significance level (Sig.) of 0.989 (greater than 0.01). This indicates no significant differences between the expected values provided by the model and the actual values, which is a positive indicator of the model's fit. The skewness test also showed similar results, with a chi-squared value of (2.678) with the same degrees of freedom and a significance level of 0.994 (also greater than 0.01). This reinforces the model's reliability and confirms that it explains the data well without significant statistical deviations. Therefore, it can be concluded that the model has good explanatory power and can be relied upon to analyze the relationship between the independent variables and the ordinal dependent variable with high statistical confidence.

6.7.8 Measuring the Explanatory Power of the Model for Fuzzy Data:

The Cox and Snell, Nagelkerke, and McFadden tests were used to test the explanatory power of the model in fuzzy data to explain the variance in the dependent variable, as shown in Table (25).

Table (25) shows the results of the Pseudo R-Square test for measuring the explanatory power of the model to explain the variance in the dependent variable for fuzzy data.

Cox and Snell	.904
Nagelkerke	1.000
McFadden	1.000

Table (25) indicates the results of the (Pseudo R-Square) measures, as it showed that the ordinal logistic regression model has very high explanatory power, as the value of (Cox and Snell) reached the maximum of (0.904), which is very close to 1, and indicates that the model has an excellent fit, and (Nagelkerke) and (McFadden) reached (1.000), which indicates that the model explains 100% of the variance in the dependent variable according to these two measures. These values, in general, reflect that the model achieves an almost perfect match between the expected and actual values, and shows a very strong predictive ability, which enhances confidence in the validity of the model and its use in explanation and prediction based on the input independent variables.

6.7.9 Estimating the Multiple Ordinal Logistic Regression Model for Fuzzy Data:

Table (26) shows the estimated values of the coefficients under fuzzy data.

Table (26) Estimated Parameters under Multiple Ordinal Logistic Regression for Fuzzy Data

		Estimate	Std. Error	Df	Sig.
Threshold	[y = 1]	21.252	3.357	1	.000
	[y = 2]	34.865	5.107	1	.000
	[y = 3]	50.196	7.163	1	.000
	[y = 4]	65.009	8.252	1	.000
Location	x1	3.627	.567	1	.000
	x2	3.768	.566	1	.000
	x3	3.709	.560	1	.000
	x4	3.710	.564	1	.000

Table (26) shows the estimated parameters using ordinal logistic regression. It reveals that the threshold estimates increase progressively from 21.252 for [y = 1] to 65.009 for [y = 4], reflecting an increasing influence of independent factors on different levels of insomnia. The standard error of the thresholds ranges from 3.357 to 8.252, indicating high accuracy in the estimates. All thresholds showed high statistical significance (Sig. =

0.000) with high estimate values, indicating clear and distinct gaps between categories and that the model effectively differentiates between the various ranks of the dependent variable. As for the independent variables x_1, x_2, x_3, and x_4, they all had positive estimate values, meaning they had a positive effect on the probability of moving to a higher category of the dependent variable. All of these values were also significant (Sig. = 0.000), demonstrating that their effect was not due to chance. The equation for multiple ordinal logistic regression for estimated fuzzy data is written as follows:

$$\text{Logit}\left(P(Y \leq K)\right) = \hat{\alpha}_j - \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \hat{\beta}_3 x_3 + \hat{\beta}_4 x_4 \quad ; j=1, 2, 3, 4 \qquad (33)$$

The four estimated equations for the five alternatives for fuzzy data are as follows:

$$\text{Logit}\left(P(Y \leq 1)\right) = 21.252 - 3.627x_1 + 3.768x_2 + 3.709x_3 + 3.710x_4 \qquad (34)$$

$$\text{Logit}\left(P(Y \leq 2)\right) = 34.865 - 3.627x_1 + 3.768x_2 + 3.709x_3 + 3.710x_4 \qquad (35)$$

$$\text{Logit}\left(P(Y \leq 3)\right) = 50.196 - 3.627x_1 + 3.768x_2 + 3.709x_3 + 3.710x_4 \qquad (36)$$

$$\text{Logit}\left(P(Y \leq 4)\right) = 65.009 - 3.627x_1 + 3.768x_2 + 3.709x_3 + 3.710x_4 \qquad (37)$$

From equations (34) to (37), the following becomes clear:

1. In equation (34), the probability of an individual's insomnia level being in the category of (never) or lower (the lowest category) is calculated. The high positive values of the coefficients associated with insomnia symptoms, environmental factors, daily habits, and psychological and health influences indicate that any increase in these factors reduces the probability of the individual remaining in the (never) category and pushes them towards higher categories of insomnia. This means that these factors contribute to the progression from not suffering from insomnia to its onset.
2. In equation (35), the probability of an individual's insomnia level being (rare) or lower (i.e., (never) or (rare) is calculated. With the same independent variables maintaining positive coefficients, this indicates that the more pronounced these factors become, the lower the probability of the individual remaining in the lower two categories and the higher the chances of moving to more severe categories of insomnia, such as (sometimes) or more frequently. This confirms the cumulative effect of these factors.
3. In Equation (36), the Logit represents the probability of the insomnia level being (sometimes) or less (i.e., never, rarely, or sometimes). With a high value for the constant and positive coefficients for the variables, it is clear that increasing these factors makes it more likely that the individual will move from intermediate to higher levels, such as "often," reflecting a gradual and clear increase in their impact.
4. In Equation (37), the Logit calculates the probability of the insomnia level being (often) or less (i.e., in any category except (always). With all coefficients being positive, the high values of the independent variables indicate a high probability of the individual moving to the highest category, (always). This means that these four factors are strongly and consistently associated with the deterioration of sleep and the development of persistent and severe insomnia in the individual.

6.8 Estimating the Ordinal Logistic Regression Model for a Granular Fuzzy Sample:

The concept behind a granular fuzzy sample is to organize fuzzy data into groups (granules). Each group is considered an analytical unit with fuzzy characteristics related to membership due to overlapping boundaries or internal differences.

Table (27) shows the sample's division into granules.

Table (27) Sample Division into Granules

The unit (the beloved)	**Number of forms**	**Participant**
College of Nursing	40	1-40
College of Management and Economics	45	41-85
Faculty of Science	40	86-125
College of Education	40	126-165
Middle Euphrates District	35	166-200
Sum	**200**	**-**

For the purpose of performing multiple ordinal logistic regression analysis on a granular fuzzy sample, the analysis will consider the granule as representing the whole or circle, which represents the granular level, and grouping will be done according to the granule (A_i^j):in subgroups:

College of Nursing = A_1^1

College of Administration and Economics = A_2^1

College of Science = A_3^1

College of Education = A_4^1

Middle Euphrates Department = A_5^1

All of these are within the granular level j=1 according to the type of kidney/circuit.

Multiple ordinal logistic regression analysis can be performed with all granules included as an additional variable within the model. This method is more statistically accurate because it considers the differences between granules within the model as a whole and reduces the loss of statistical significance resulting from subgrouping. This is achieved by coding the granule (e.g., College of Nursing, Management and Economics, etc.) as a categorical variable within the model, and then including this variable with the other independent variables in the ordinal logistic regression analysis.

Table (28) shows the estimated values of the coefficients under fuzzy granular data.

Table (28) Estimated Parameters by Ordinal Logistic Regression for Fuzzy Granular Data

Type	Predictor	Estimate	Std. Error	Sig.
Threshold	[y = 1]	5.75	1.27	0.000
	[y = 2]	4.80	1.36	0.000
	[y = 3]	4.89	1.43	0.000
	[y = 4]	4.81	2.04	0.000
Location	x1	3.67	0.15	0.000
	x2	4.33	0.27	0.000
	x3	4.47	0.04	0.000
	x4	4.60	0.02	0.000
	College of Management and Economics	0.41	1.27	0.000
	College of Education	0.21	1.36	0.000
	College of Nursing	0.11	1.33	0.000
	Faculty of Science	0.32	1.04	0.000
	Middle Euphrates District	0.21	1.33	0.000

Table (28) shows that the included variables have a strong influence on the predicted probabilities. In the estimates from academic institutions such as the College of Management and Economics, the College of Education, the College of Nursing, and the College of Science, all these variables have a positive impact on the prediction. All values in the statistical significance column (Sig.) are 0.000, reflecting strong statistical significance for both the thresholds and positional variables, thus reinforcing the importance of these variables in predicting insomnia outcomes.

The estimated multiple ordinal logistic regression equation for a granular fuzzy sample is written as follows:

$$\text{Logit}\left(P(Y \le K)\right) = \hat{\alpha}_j - \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \hat{\beta}_3 x_3 + \hat{\beta}_4 x_4 + \hat{\beta}_4 A_1^1 + \hat{\beta}_5 A_2^1 + \hat{\beta}_6 A_3^1 + \hat{\beta}_7 A_4^1 + \hat{\beta}_8 A_5^1 \quad (38)$$

The four estimated equations for the five alternatives of granular fuzzy data are as follows:

$$\text{Logit}\left(P(Y \le 1)\right) = 5.7 - 3.67x_1 + 4.33x_2 + 4.47x_3 + 4.60x_4 + 0.41A_1^1 + 0.21A_2^1 + 0.11A_3^1 + 0.32A_4^1 + 0.21A_5^1 \quad (39)$$

$$\text{Logit}\left(P(Y \le 2)\right) = 4.80 - 3.67x_1 + 4.33x_2 + 4.47x_3 + 4.60x_4 + 0.41A_1^1 + 0.21A_2^1 + 0.11A_3^1 + 0.32A_4^1 + 0.21A_5^1 \quad (40)$$

$$\text{Logit}\left(P(Y \le 3)\right) = 4.89 - 3.67x_1 + 4.33x_2 + 4.47x_3 + 4.60x_4 + 0.41A_1^1 + 0.21A_2^1 + 0.11A_3^1 + 0.32A_4^1 + 0.21A_5^1 \quad (41)$$

$$\text{Logit}\left(P(Y \le 4)\right) = 4.81 - 3.67x_1 + 4.33x_2 + 4.47x_3 + 4.60x_4 + 0.41A_1^1 + 0.21A_2^1 + 0.11A_3^1 + 0.32A_4^1 + 0.21A_5^1 \quad (42)$$

From equations (39) to (42), the following becomes clear:

1. In equation (39), the Logit factor calculates the probability of the insomnia level being (rare) or lower, i.e., (never) or (rare). With the same independent variables having positive coefficients, this indicates that the more severe these factors become, the lower the probability of the individual remaining in the lower two categories, and the higher the chances of moving to more severe insomnia categories such as "sometimes" or more frequently. This confirms the upward effect of these factors.
2. In Equation (40), the Logit represents the probability of the insomnia level being "sometimes" or less (i.e., never, rarely, or sometimes). With a high value for the constant and positive coefficients for the variables, it is clear that increasing these factors makes it more likely that the individual will move from intermediate to higher levels, such as "often," reflecting a gradual and clear increase in their impact.
3. In Equation (41), the Logit calculates the probability of the insomnia level being "often" or less (i.e., in any category except "always"). With all coefficients being positive, the high values of the independent variables indicate a high probability of the individual moving to the highest category, "always." This means that these four factors are strongly and consistently associated with the deterioration of sleep and the development of persistent and severe insomnia in the individual.

6.9 Calculating the probability of insomnia using multiple ordinal logistic regression models:

Table (29) shows the results of the probability of insomnia according to multiple Ordinal logistic regression models.

Table (29) Probability of insomnia according to multiple Ordinal logistic regression model estimates for conventional, fuzzy, and granular fuzzy data for a probability of Logit $\left(P(Y \le 4)\right)$

Granular	Fuzzy	Traditional
0.01851	0.02314	0.07166
0.97729	0.98921	0.99744
0.02185	0.03973	0.02885
0.98085	0.99132	0.99492
0.01934	0.02885	0.05970
.	.	.
.	.	.

.	.	.
0.97190	0.95993	0.91946
0.00053	0.01991	0.03651
0.96161	0.96720	0.96812
0.97150	0.97776	0.95856
0.01967	0.03569	0.09699

Table (30) Standard Error of Multiple Ordinal Logistic Regression Models for Traditional, Fuzzy, and Granular Fuzzy Data

std Method	Traditional	Fuzzy	Granular
[y = 1]	3.357	2.454	1.27
[y = 2]	5.107	3.042	1.36
[y = 3]	7.163	4.167	1.43
[y = 4]	9.252	5.181	2.04
x1	0.567	0.363	0.15
x2	0.566	0.35	0.27
x3	0.560	0.388	0.04
x4	0.564	0.389	0.02
College of Management and Economics	-	-	1.27
College of Education	-	-	1.36
College of Nursing	-	-	1.33
Faculty of Science	-	-	1.04
Middle Euphrates District	-	-	1.33

Table (29) presents the probabilities of insomnia according to the estimates of the multiple ordinal logistic regression models for conventional, fuzzy, and granular data. We observe that the conventional estimates differ significantly from the fuzzy and granular estimates. For example, in the estimates related to the [y = 1] level, the probability in the conventional model is 0.07166, while in the granular model it is 0.01851, reflecting that the conventional model provides higher estimates. The data also show that the granular model tends to provide lower estimates across all points compared to the other models, suggesting that it may be more conservative in estimating the probabilities of insomnia.

Table (30) displays the standard error of several ordinal logistic regression models for conventional, fuzzy, and granular datasets. It shows that the granular model gives the highest accurate estimates when compared to the conventional and fuzzy models for different categories and variables. For instance, the standard error values in the granular model are much lower at the [y = 1], [y = 2], [y = 3], and [y = 4] levels than they are in the conventional and fuzzy models. This shows that the granular model makes superior predictions. In the same way, estimates for variables like x1, x2, x3, and x4 show a noticeable difference in standard error. The granular model has lower standard error values than the conventional and fuzzy models, which means it is more accurate. The standard error for several colleges, such the College of Management and Economics and the College of Nursing, was also determined using solely the granular model. This shows that the granular model is clearly better at getting more accurate estimates in all categories.

6. Conclusions:

1. The multiple ordinal logistic regression models using granular data provided more accurate estimates compared to

traditional and fuzzy models across different categories and variables. The fuzzy model showed more accurate estimates than the traditional model.

2. Estimates in the traditional model were higher than those in the granular model in most cases, indicating that the traditional model may overestimate probabilities compared to the granular model, which provides more conservative estimates.
3. Insomnia is a common problem among the participants, manifesting in various ways such as difficulty falling asleep, early awakenings, or restless sleep.
4. Insomnia overlaps with psychological factors such as stress, anxiety, and depression, indicating a strong correlation between psychological state and sleep quality.
5. There are clear physical effects of insomnia, such as daytime fatigue and exhaustion, frequent headaches, and decreased concentration. 6. Unhealthy daily habits such as caffeine consumption, irregular sleep schedules, and using electronic devices before bed contribute to worsening insomnia.
6. The sleep environment, including noise, lighting, and temperature, directly affects sleep quality for many individuals.
7. Although a large number of participants felt they had a sleep problem, a significant percentage lacked awareness regarding the severity or causes of their insomnia.
8. Insomnia is not an isolated condition but rather a multifactorial one, requiring a comprehensive intervention that includes behavior modification, lifestyle improvements, and attention to mental health.

6. Recommendations:

Granular Ordinal logistic regression modelling is recommended for future studies on insomnia. This model is expected to be a reliable tool for predicting insomnia cases and better identifying contributing factors.

Intervention programs should be developed that focus on improving mental health and promoting healthy habits, such as stress reduction and lifestyle improvements.

Launch awareness campaigns aimed at correcting behavioural habits such as caffeine consumption and electronic device use among individuals, especially in academic settings.

Expand research to include the impact of social factors such as the work environment and family relationships on insomnia. This information can help tailor treatment more effectively, particularly in societies experiencing high levels of stress.

Conduct larger studies to confirm these findings and accurately analyse the impact of insomnia on public health. The sample size should also be broadened to include diverse segments of society to improve the accuracy of the results.

Increase investment in developing behavioural therapy techniques and training specialists to provide more specialized and effective solutions for individuals with insomnia.

Given the success of the questionnaire in data collection, it is recommended that the instrument be continuously improved based on feedback from reviewers and participants to ensure it meets all research needs.

There is a need to enhance psychological and health education about sleep disorder and provide specialized support for individuals suffering from chronic insomnia.

References:

1. Al-Azzi, Muhammad Shakir Mahmoud, "Distinctive Analysis and Logistic Regression Using Partial Least Squares," Department of Statistics, College of Administration and Economics, University of Baghdad, (2018).

2. Al-Fatlawi, Sara Amer Mahmoud, "Using Ordinal Logistic Regression to Identify the Most Important Factors Affecting Household Income," Published Master's Thesis, Department of Statistics, College of Administration and Economics, University of Karbala, (2019).

3. Baraa Salim, Muhammad Taher Anan, Muhammad Bashar Zeina, "A Comparison of Classification Using Classical Logistic Regression and Fuzzy Logistic Regression: A Case Study of Type 2 Diabetes Patients," Aleppo University Journal of Research, Issue 160, (2022). 4. Jabbar, Ahmed Saeed, "Bayesian Estimation of Ordinal Logistic Regression," Master's Thesis, published, Department of Statistics, College of Administration and Economics, University of Karbala, (2021).
4. Ali, Bashar Khalid, "Testing for the Best Estimation of Fuzzy Reliability for the Fregett Distribution," Master's Thesis, unpublished, Department of Statistics, College of Administration and Economics, University of Karbala, (2018).
5. Ali, Bashar Khalid, "A General Robust Bayesian Fuzzy Method for Probability Distributions," Doctoral Dissertation, unpublished, Department of Statistics, College of Administration and Economics, University of Karbala, (2022).
6. Da'ish, Muhammad Amin, "The Logistic Regression Model: Its Concept, Characteristics and Applications", Al-Siraj Journal of Education and Community Issues in Algeria, Issue 1, pp. 124-132, (2017).
7. Al-Khairullah, Najla A., &, Al-Bhidawi, H. K., " computational methods of the logistic regression" , Journal of Physics , February , (2021)
8. Aya A Mitani , Osvaldo Espin-Garcia , Daniel Fernández and Victoria Landsman, " Applying survey weights to ordinal regression models for improved inference in outcome-dependent samples with ordinal outcomes" , (2024).
9. Das, S., Rahman, R. M. ,"Application of ordinal logistic regression analysis in determining risk factors of child malnutrition in Bangladesh " Das and Rahman Nutrition Journal, PP 1-11 , (2011).
10. Derr, B. ,"Ordinal Response Modeling with the LOGISTIC Procedure" Statistics and Data Analysis, P 446, (2013).
11. Garg*, Harish; Sharma, S.P & Rani, Monica," Weibull fuzzy probability distribution for analyzing the behavior of pulping unit in a paper industry", Int. J. Industrial and Systems Engineering, Vol.14, No.4, pp395-413 (2013) .
12. Haydar , Ahmed ,Ali , "Use of logistic regression to study the most important factors affecting the incidence of tuberculosis",Journal of AL-Qadisiyah for computer science and mathematics ,Vol.10, No.2,(2018).
13. John Wiley ," Applied Logistic Regression" , Third Edition , Published simultaneously in Canada: Published by John Wiley & Sons, Inc., Hoboken, New Jersey., (2013) .
14. Juan C. Gámez-Granados[1], Aurora Esteban Francisco J, Rodriguez-Lozano, Amelia Zafra[2]," An algorithm based on fuzzy ordinal classification to predict students' academic performance",(2023).
15. Klaua, D. ,Über einen Ansatz zur mehrwertigen Mengenlehre. Monatsb. Deutsch. Akad. Wiss. Berlin 7, 859-876. A recent in-depth analysis of this paper has been provided by Gottwald, S. (2010), "An early approach toward graded identity and graded membership in set theory". Fuzzy Sets and Systems 161 (18):2369-2379.com , (1965) .
16. Kwang H. Lee, "First Course on Fuzzy Theory and Applications" ISSN 16-15-3871, ISBN 3-540-22988-4 Springer Berlin Heidelberg New York, ppt:8 , (2004) .
17. . Mesfin Esayas Lelisho1 , Abebe Argaw Wogi 2, Seid Ali Tareke 1, "Ordinal Logistic Regression Analysis in Determining Factors Associated with Socioeconomic Status of Household in Tepi Town, Southwest Ethiopia" Scientific World Journal ,(2022).

18. Sherif A. Moawed¹, Esraa Mahrous", Ahmed Elaswad², Hagar F. Gouda³, and Ahmed Fathy¹, " The Application of Ordinal Logistic Regression Model as a Robust Tool for Enhanced Prediction of Milk Yield in Dairy Cows" , SCVMJ, XXIX (1) ,(2024).

19. Tian CHEN ¹, Wan TANG , Ying LU , Xin TU ," Rank regression: an alternative regression approach for data with outliers " ,(2014).

20. Yanan Diao, Qiangqiang Chen, Yan Liu, Linjie He', Yue Sun', Xiangxin Li, Yumin Chen, Guanglin Li and Guoru Zhao," A fuzzy granular logistic regression algorithm for SEMG-based cross-individual prosthetic hand gesture classification" Journal of Neural Engineering ,(2023).

21. Voskoglou, Michael; Broumi, Said, "Applications of Intuitionistic Fuzzy Sets to Assessment and Multi-Criteria Decision Making", Journal of Fuzzy Extension and Applications www.journal-fea.com J. Fuzzy. Ext. Appl.Vol.4,No.4,p:299-309,(2023) .

22. Witold Pedrycz , Rami Al-Hmouz , Abdullah Saeed Balamash , Ali Morfeq, " Designing granular fuzzy models: A hierarchical approach to fuzzy modeling " , Knowledge-Based Systems Volume 76, , Pages 42-52, March, (2015) .

23. Zadeh, L. A., "Fuzzy Sets", Information and control, Department of Electrical Engineering and Electronics Research Laboratory, University of California, Berkeley, California, 8, 338-353, (1965).

24. Zadeh, L., A., "Outline of a New Approach to the Analysis of Complex Systems and Decision Processes", IEEE TRANSACTIONS ON SYSTEMS, MAN, AND CYBERNETICS, VOL. SMC-3, NO. 1, JANUARY,pp:28-44 , (1973) .

25. Kalan , Mohammad Ebrahimi ; Jebai Rime; Zarafshan, Elaheh, Bursac , Zoran , (2020), " Distinction Between Two Statistical Terms: Multivariable and Multivariate Logistic Regression ", Nicotine & Tobacco Research, 2020, 1–2 doi:10.1093/ntr/ntaa055 Letter Received February 18, 2020; Editorial Decision March 12, 2020; Accepted March 23, 2020 Advance Access publication March 26, 2020

26. H. Zhang, Y. He, and W. Ma, “An approximation reduction approach in multi-granulation hesitant fuzzy decision information system,” Journal of Intelligent & Fuzzy Systems, vol. 37, no. 1, pp. 1555–1567, Jul. 2019, doi: 10.3233/jifs-18586.

27. Najm, Adel Abbood, Ali , Bashar Khalid , (2024), " Survival Function Estimation for Weibull Distribution Based on Granular Hesitant Fuzzy Set ", CENTRAL ASIAN JOURNAL OF MATHEMATICAL THEORY AND COMPUTER SCIENCES https://cajmtcs.centralasianstudies.org/index.php/CAJMTCS Volume: 06 Issue: 01 | January 2025 ISSN: 2660-5309

28. Morin CM, Benca R. Chronic insomnia. Lancet. 2012 Mar;379(9821):1129–41. PMID: WOS:000302131800035.

29. Morgan K, Gregory P, Tomeny M, et al. Self-help treatment for insomnia symptoms associated with chronic conditions in older adults: a randomized controlled trial. J Am Geriatr Soc. 2012 Oct;60(10):1803–10.

30. Smith MT, Finan PH, Buenaver LF, et al. Cognitive-behavior therapy for insomnia in knee osteoarthritis: A double-blind, randomized, active placebo controlled clinical trial. Arthritis & Rheumatology. 2015. PMID.

31. Harrison CC, Solomon EM, Pellow J. The effect of a homeopathic complex on psychophysiological onset insomnia in males: a randomized pilot study. Altern Ther Health Med. 2013 Sep-Oct;19(5):38–43.

32. Van Straten A, Emmelkamp J, de Wit J, et al. Guided Internet-delivered cognitive behavioural treatment for insomnia: a randomized trial. Psychol Med. 2014 May;44(7):1521–32.