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Certification in Business Data Analytics (IIBA - CBDA)

IIBA CBDA

Version Demo

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QUESTION NO: 1

A clinical research organization is using predictive analytics to improve patient safety and decrease costs on its clinical trials. To ensure that a standard set of tools/techniques is identified and best practices adhered to, teams are required to create scenarios to generate appropriate data for initial analysis. This practice is required because it is almost certain that data will be difficult to come by for most research. Which concern would lead the team to establish scenario development as a required technique?

A. Data validity

B. Data privacy

C. Data reliability

D. Data reproducibility

ANSWER: A

Explanation:

Data validity is correct because the organization must ensure that data used to train, test, and interpret predictive models is appropriate for the clinical-trial questions being examined. When historical or observational trial data is sparse, scenario development provides structured, plausible situations from which an initial analytical data set can be derived. The scenarios should reflect relevant clinical conditions, patient characteristics, operational events, assumptions, and expected outcomes. This makes it possible to assess whether the available or generated data meaningfully represents the phenomenon that the predictive analysis is intended to model.

In business data analytics, validity concerns whether data is fit for its intended analytical purpose and supports sound conclusions. Requiring a consistent scenario-development technique establishes a repeatable way to define assumptions and generate data that is relevant to the decision context before models are relied upon for safety or cost decisions. This is particularly important in clinical research, where analytical conclusions must be credible and grounded in data that accurately represents the intended clinical concepts. IIBA describes CBDA as a framework for applying analysis practices to guide data-driven decisions: IIBA CBDA certification. Clinical data should also be reliable and accurately attributable, as emphasized in the FDA's data-integrity guidance: FDA Data Integrity and Compliance With Drug CGMP.

QUESTION NO: 2

An online retailer of men's athletic apparel is seeking to become the market leader in the industry. To deliver on this strategy, the analytics team continuously collects data on the prices of competitorproducts and uses this information to adjust the retailer's prices. What type of analytics is the retailer using to maintain their pricing structure?

A. Descriptive

B. Diagnostic

C. Predictive

D. Prescriptive

ANSWER: D

Explanation:

Prescriptive is correct because the retailer is using competitor-price data as an input to determine and implement an appropriate pricing action. Prescriptive analytics focuses on recommending or selecting what should be done to achieve a desired business outcome. In this case, the desired outcome is strengthening competitive position and supporting the strategic objective of market leadership; the action is adjusting the retailer's prices in response to observed market pricing.

Business data analytics commonly distinguishes this type of analysis from reporting on past events or estimating future outcomes: prescriptive work uses analytical findings, decision rules, optimization, or models to guide a decision and a course of action. Continuously monitoring competitors and changing prices accordingly is therefore a pricing decision process, not merely the collection or presentation of competitor data. The retailer can use this approach to balance competitive positioning, margin objectives, demand considerations, and pricing constraints as conditions change.

This aligns with IIBA's description of business data analytics as enabling organizations to make better decisions and take action based on data. See [IIBA's Certification in Business Data Analytics (CBDA)] overview and the [Understanding the Guide to Business Data Analytics].

QUESTION NO: 3

The analytics team is struggling with which recommendation to make. Their challenge is that they have five good options and this indecision is stopping them from moving forward. To help the team finalize their recommendation, the BA professional on the team recommends they complete:

A. Root cause analysis

B. Business rules analysis

C. Data flow diagrams

D. Acceptance and evaluation criteria

ANSWER: D

Explanation:

Acceptance and evaluation criteria are the appropriate technique because the team has already identified several viable alternatives and now needs a structured, evidence-based way to select the recommendation that delivers the most value. These criteria establish the measures by which each option will be assessed, such as expected business benefits, alignment with objectives, feasibility, implementation cost, delivery time, risk exposure, stakeholder impact, data quality implications, and regulatory or operational constraints. Defining the criteria before choosing among the alternatives makes the decision transparent, consistent, and traceable to stakeholder needs. The team can weight the criteria where appropriate, score each of the five options against the agreed measures, and document the resulting trade-offs. This converts an impasse caused by several "good" choices into a defensible recommendation supported by explicit evidence. It also gives decision makers a clear rationale for approving the selected course of action and a basis for confirming whether the delivered result is acceptable. This aligns with the CBDA focus on using analysis results to influence business decision making and with business-analysis practices for evaluating solution alternatives. See the [IIBA CBDA certification overview] and the [IIBA Business Analysis Standard].

QUESTION NO: 4

An organization's customers are categorized based on the amount of purchases completed over the last 12 months. The analytics team would like to ensure the accuracy of their survey results and decide to randomly select 500 customers to participate in a survey from this large pool of customers. This is an example of:

A. Stratified sampling

B. Quota sampling

C. Purposive sampling

D. Snowball sampling

ANSWER: A

Explanation:

Stratified sampling is appropriate because the customer population has first been organized into groups using a meaningful characteristic: purchase amount during the preceding 12 months. Those groups form strata, such as low-, medium-, and high-purchase customers. A random sample is then drawn in a way that includes customers from the defined strata, commonly in proportion to each stratum's size or according to an intentional allocation rule. This approach helps the survey reflect important differences across the customer base rather than allowing a large or highly variable population to be represented unevenly.

For business data analytics, the relevant point is that the segmentation variable is known before selecting survey participants and is used to structure a probability-based sample. The resulting survey can therefore support more dependable estimates for the overall customer population and, where needed, for the purchase-based groups themselves. This aligns with the CBDA focus on selecting data-collection approaches that produce sufficiently representative, decision-useful evidence. The International Institute of Business Analysis describes the CBDA certification and its business data analytics scope at IIBA CBDA Certification. Additional technical guidance on stratified random sampling is available in the NIST/SEMATECH e-Handbook.

QUESTION NO: 5

An analytics team employed at a leading credit card company is utilizing data analytics to identify unusual credit card purchases.

They have created the following visual. How many extreme outliers exists in this dataset?

A. 0

B. 5

C. 3

D. 2

ANSWER: C

Explanation:

3 is correct because the visual identifies three observations that lie distinctly apart from the main concentration of data points. In a credit-card analytics context, these isolated observations represent purchases whose expense values are unusually high relative to the income values represented in the chart. Their separation from the broader pattern is the important feature: they are not simply observations near the edge of the typical spread, but extreme values that merit further investigation for possible fraud, exceptional customer behavior, data-entry issues, or other business-relevant causes.

Business data analytics uses visualization to help analysts recognize patterns, anomalies, and relationships before deciding whether further analysis or action is warranted. Identifying these three extreme observations supports the stated goal of detecting unusual purchases and provides a focused set of transactions for review. Outlier identification is a standard exploratory-data-analysis activity; NIST describes outliers as observations that appear inconsistent with the remainder of a data set and notes the importance of investigating them in context. See the NIST Engineering Statistics Handbook discussion of outliers and IIBA's Business Data Analytics certification overview.

QUESTION NO: 6

The analytics team has been asked to provide an estimate of the number of customers they expect to have in 12 months. They debated how accurate that figure needs to be and determined that based on the availability of good data, they could predict within + or - 10%. This is an example of a:

A. ROM estimate

B. Delphi estimate

C. Parametric estimate

D. Definitive estimate

ANSWER: D

Explanation:

Definitive estimate is correct because the team has sufficient, reliable data and has established a relatively narrow expected accuracy range of plus or minus 10 percent. A definitive estimate is a detailed, data-supported estimate used when uncertainty has been reduced enough to support a dependable forecast and informed decision-making. In this case, the estimate concerns the expected customer count over the next 12 months, but the classification is driven primarily by the level of precision and quality of information available—not by whether the subject is cost, effort, schedule, or customer volume. A stated tolerance of approximately 10 percent represents a high-confidence estimate compared with early, broad planning estimates. The team has also explicitly considered the required accuracy and confirmed that good data is available, both of which are essential elements of producing a definitive estimate. Estimation should communicate an expected value together with an appropriate range, allowing stakeholders to understand the forecast's usable precision and make decisions proportionate to its uncertainty. This aligns with established project-estimating practice, where definitive estimates are developed from more complete information and have narrower accuracy ranges. See the Project Management Institute's guidance on project cost estimating and the IIBA BABOK Guide resources.

QUESTION NO: 7

A large retail chain has asked their analytics team to complete a study on their customers' purchasing patterns. The analyst assigned to the study has decided to draw further insight by grouping customers based on their purchasing habits.This clustering approach is an example of:

A. Untrained learning

B. Trained learning

C. Unsupervised learning

D. Supervised learning

ANSWER: C

Explanation:

"Unsupervised learning" is correct because clustering identifies naturally occurring groups within data when no preassigned target, label, or outcome is provided. In this case, the retail chain wants to understand purchasing patterns, and the analyst groups customers according to similarities in their buying habits. The analysis is therefore discovering structure already present in the customer data rather than learning to predict a known value, such as whether a customer will make a purchase or respond to a campaign. Clustering can create actionable customer segments based on features such as purchase frequency, average order value, product categories purchased, recency of transactions, and channel preferences. Those segments can then support business decisions such as tailoring promotions, improving product assortment, or designing retention initiatives. IIBA's business data analytics material identifies unsupervised learning as an approach for finding patterns and relationships in data without predefined outcomes, with clustering being a common technique. The general machine-learning definition is also consistent with this use: unsupervised algorithms derive patterns from unlabeled datasets. See the IIBA Guide to Business Data Analytics and scikit-learn's clustering documentation.

QUESTION NO: 8

A data scientist is performing statistical analysis and is interested in graphically depicting the data set according to the associated quartiles Minimum, First Quartile, Median, Second Quartile, Third Quartile. Which technique would allow for the display of this statistical five number summary?

A. Gaussian distribution

B. Scatter plot

C. Multivariate histogram

D. Box plot

ANSWER: D

Explanation:

Box plot is the appropriate technique because it visualizes the five-number summary of a data set: the minimum, first quartile, median, third quartile, and maximum. The box extends from the first quartile to the third quartile, representing the interquartile range and the middle half of the observations. A line within the box identifies the median. Whiskers extend from the box to show the spread of values at the low and high ends; depending on the selected convention, values beyond a defined distance from the quartiles may be displayed separately as outliers. This makes a box plot particularly useful during statistical analysis to quickly assess central tendency, variability, distributional spread, potential skewness, and unusual observations. It also supports clear comparison of these characteristics across multiple categories or groups by placing several box plots side by side. The technique is therefore directly aligned with the request to graphically display quartile-based summary statistics. See the NIST Engineering Statistics Handbook discussion of box plots and the NIST definition of the five-number summary.

QUESTION NO: 9

The results of the data analytics work led to some clear and strongly supported outcomes and the analytics team is very confident in their recommendations; particularly given that the payback on the required changes are a short 3 months. However, there is concern because the organization operates in a highly regulated environment and some new regulatory changes are being considered with announcements and implementation in the next 6 months. Under these conditions the team decides to:

A. Recommend no action be taken at this time and revisit in 6 months

B. Reassess their results to ensure their validity and then decide what to do

C. Identify and carefully document assumptions for their recommendation

D. Postpone recommendations for 6 months until the announcements are made

ANSWER: C

Explanation:

Identify and carefully document assumptions for their recommendation is the appropriate response because the prospective regulatory changes are a material source of uncertainty that could affect both the feasibility and value of the proposed changes. The team has credible analytical results and a short expected payback period, so it should present the recommendation rather than automatically defer action. However, responsible data-driven decision making requires decision makers to understand the conditions on which the recommendation depends. The documented assumptions should address relevant regulatory scenarios, expected timing, potential effects on the proposed solution, and the point at which a regulatory development would require the organization to reassess or alter its course. This makes the analysis transparent and supports an informed decision that balances near-term benefits with regulatory exposure. It also enables monitoring: as announcements or implementation details become available, stakeholders can compare them to the stated assumptions and update the recommendation efficiently. IIBA’s business data analytics guidance emphasizes communicating insights, limitations, and assumptions so that stakeholders can make decisions with an appropriate understanding of analytical uncertainty. See IIBA’s Business Data Analytics resources and the IIBA-CBDA Handbook.

QUESTION NO: 10

A software company launched a new product in late 2016. The product manager is reviewing a Box and Whisker plot used to compare year-over-year sales, from 2017 to 2018. What is the conclusion he can make from this chart?

A. 2017 minimum and maximum sales are higher than 2018, and the 2017 median result ishigher than the 2018 median result

B. 2017 minimum and maximum sales are higher than 2018, but the 2017 median result islower than 2018 1st quartile result

C. 2018 minimum and maximum sales are higher than 2017, and the 2018 quartile results arehigher than 2017 quartile results

D. 2018 minimum and maximum sales are higher than 2017, and the 2018 1st quartile ishigher than 2017 median result

ANSWER: D

Explanation:

2018 minimum and maximum sales are higher than 2017, and the 2018 1st quartile is higher than 2017 median result is the supported conclusion. A box-and-whisker plot summarizes a distribution using its minimum, first quartile, median, third quartile, and maximum. The whisker endpoints identify the displayed minimum and maximum values, while the lower edge of each box represents the first quartile. In the chart, the displayed 2018 whisker endpoints are above their 2017 counterparts, showing that both the minimum and maximum observed sales are higher in 2018. In addition, the lower edge of the 2018 box is positioned above the median line within the 2017 box. This means that the sales value at the 25th percentile for 2018 exceeds the 50th-percentile, or median, sales value for 2017. This comparison gives the product manager a concise, evidence-based view that the 2018 sales distribution shifted upward relative to 2017, including its lower-end sales performance. For definitions of quartiles and the graphical components of a box plot, see the NIST Engineering Statistics Handbook: Box Plot and IBM documentation on box plots.

QUESTION NO: 11

An analytics team is comparing two proposed process changes. Both are expected to generate the same total net benefit over five years. Option A requires most implementation costs in the first year and produces benefits later. Option B has lower initial costs and begins producing benefits in the first year. If the organization considers the time value of money, which analysis should the team use to compare the options?

A. Payback period

B. Net present value

C. A simple comparison of total undiscounted benefits

D. Break-even analysis only

ANSWER: B

Explanation:

Net present value is correct because it converts future costs and benefits into present-day values using an appropriate discount rate. Although the options have the same undiscounted total net benefit, the timing of cash flows differs. Earlier benefits and later costs generally have greater present value than later benefits and earlier costs.

Payback period can show how quickly an initial investment is recovered, but it does not fully compare all costs and benefits over the five-year horizon. A simple total-benefit comparison ignores timing. Break-even analysis identifies when cumulative benefits equal cumulative costs, but it does not provide the same complete discounted comparison of both alternatives.

QUESTION NO: 12

A data dictionary is being developed for a dataset describing a company's customer base. Within the data dictionary, which of the following represents a composite data element?

A. Street address

B. First name

C. Total sale

D. Birthdate

ANSWER: A

Explanation:

Street address is a composite data element because it can be represented as one business attribute while being composed of several meaningful subordinate parts. In a customer dataset, those parts commonly include a building or street number, street name, unit or apartment identifier, city, state or province, postal code, and country. A data dictionary may document the overall address as a single element for business use and, where needed, also define its component elements, structure, permitted formats, and validation rules.

This distinction is important in business data analytics because an address may need to be displayed or exchanged as one value, yet its individual components support analysis, customer matching, geographic segmentation, delivery, data-quality checks, and regulatory reporting. Defining the element as composite makes the relationship between the whole value and its parts explicit, helping analysts and stakeholders use it consistently. Structured business-message standards similarly distinguish composite data elements from simple elements and define composites as structures containing component data elements; see the UN/EDIFACT Syntax Rules (ISO 9735). IBM's overview of data elements also illustrates the importance of documenting business data definitions and their characteristics in governed data assets.

QUESTION NO: 13

After analyzing sales data, the analytics team finds that the older the customer, the more expensive the neckties purchased. The team felt this was a breakthrough insight but on closer analysis realized that other factors could account for this relationship. This is a clear indication that:

A. Correlation between variables implies causation

B. Causation has no relationship with correlation

C. Causation between variables does not imply correlation

D. Correlation between variables does not imply causation

ANSWER: D

Explanation:

Correlation between variables does not imply causation is correct because the observed pattern shows an association: customer age and the price of neckties purchased tend to increase together in the available data. That association alone does not establish that being older causes a customer to buy more expensive neckties. A causal conclusion requires further evidence and analysis to account for plausible confounding variables, such as disposable income, occupation, purchasing channel, brand preference, or the type of event for which the necktie was bought. These factors may influence both age and spending, creating or strengthening an apparent relationship even when age is not the direct cause. Sound business data analytics therefore distinguishes descriptive or correlational findings from validated causal claims. The team should frame this as a hypothesis, identify potential confounders, and use an appropriate design or analytical method—such as controlled experimentation, stratification, or causal analysis—to evaluate whether a causal effect is supported. This distinction helps decision-makers avoid implementing actions based on relationships that may not persist when underlying drivers are considered. See the IIBA Business Analysis Standard for evidence-based business analysis principles and the CDC discussion of association and causation for the distinction between observed associations and causal inference.

QUESTION NO: 14

With the recent departure of two of its employees, an IT helpdesk team is now understaffed and finding it difficult to keep up with the current workload. The number of tickets being received has increased as well as the number of days to resolve the tickets. The IT manager has set up a meeting with the IT director to request funding for two new helpdesk agents. To prepare for the

meeting, the manager is interested in showing the tickets processed against ticket volume over the past year. What type of chart should the manager use to effectively show the change in processing rate over time?

A. each month, over the past year

B. each month, since June

C. against the number coming over the past year

D. processed as of year to date

ANSWER: C

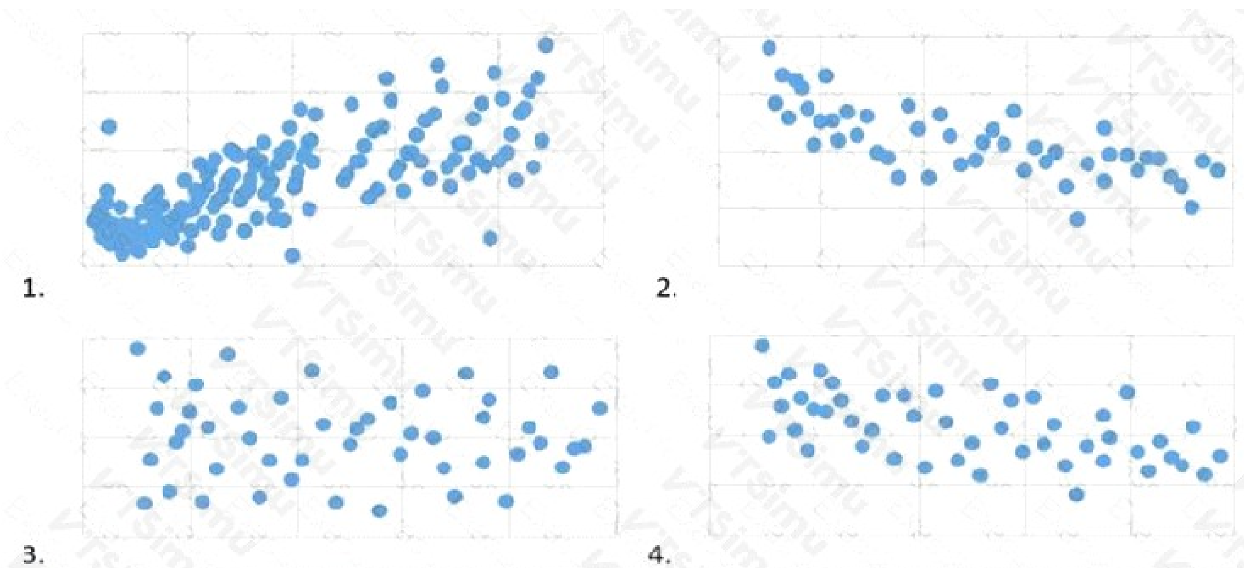
Explanation:

“against the number coming over the past year” is correct because the manager needs to communicate the relationship between incoming demand and completed work across a continuous time period. A line chart with two monthly series—tickets received and tickets processed—makes the helpdesk’s processing rate and capacity trend visible. Plotting both measures against the same monthly timeline lets the director readily see whether completions are keeping pace with arrivals, whether the gap is widening, and whether any changes are sustained or seasonal. This directly supports an evidence-based funding request: a persistent excess of incoming tickets over processed tickets demonstrates an accumulating workload, while changes in the distance between the series show how the team’s ability to handle demand has evolved. The reported increase in resolution days provides useful supporting context, but the two time-series measures provide the clearest visual evidence of throughput relative to demand. Interpreting and communicating data through suitable visualizations is a core part of business data analytics reporting, as described in the [IIBA Guide to Business Data Analytics](). For general guidance on using line charts to show trends over time, see [Tableau’s line chart documentation]().

QUESTION NO: 15

DIAGRAM TAKEN

A data scientist is analyzing a dataset to determine if there is a strong relationship between two variables. A measure of covariance is done. Which of the following graphs indicate Zero Covariance between variables?



A. 3

B. 1

C. 4

D. 2

ANSWER: C

Explanation:

4 is correct because its points are scattered without an overall upward or downward linear direction. Covariance measures whether two variables tend to vary together around their respective means. It is calculated from the average product of the variables’ deviations from those means. In graph 4, positive and negative cross-deviations occur without a consistent directional pattern, so they balance approximately to zero. Consequently, the graph represents zero covariance and no linear association between the variables.

For visual interpretation in business data analytics, a positive covariance is associated with a general co-movement upward, while a negative covariance is associated with one variable tending to decrease as the other increases. A scatterplot with no directional linear tendency, as shown by graph 4, is therefore the appropriate representation of a covariance near zero. Importantly, zero covariance establishes the absence of a *linear* relationship; it does not, by itself, prove that the variables are independent, because a non-linear relationship can still be present. This distinction helps analysts avoid concluding that no relationship of any kind exists solely from a zero covariance result. See the NIST discussion of covariance and the Penn State overview of correlation and linear relationships.

QUESTION NO: 16

A colleague proposes measuring job satisfaction by asking the question "What is your salary?". What is the concerning factor about this question?

A. Validity

B. Clarity

C. Reproducibility

D. Subjectivity

ANSWER: A

Explanation:

Validity is the concerning factor because the proposed question does not adequately measure the construct it is intended to represent: job satisfaction. In business data analytics, validity concerns whether a measurement instrument actually captures the concept that the analysis seeks to assess. Salary is a factual, generally clear, and potentially useful data point, but it is only one possible influence on how satisfied a person feels with their job. Job satisfaction is broader and can encompass perceptions of the work itself, relationships, recognition, autonomy, workload, development opportunities, and workplace conditions. Asking only about salary therefore does not provide a sufficiently direct or comprehensive measure of job satisfaction. A valid approach would operationalize job satisfaction through one or more questions designed to assess employees' attitudes or overall satisfaction with their work, rather than substituting a related but distinct variable. This distinction is important because conclusions are only as sound as the measures used to produce them; using salary as a proxy could lead stakeholders to draw unsupported conclusions about employees' satisfaction. IIBA's business data analytics framework emphasizes assessing the quality and fitness of data and measures for their intended analytical purpose. See the IIBA standards and resources and the overview of validity in research.