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Differences in ischemic heart disease between males and females using predictive artificial intelligence models

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ABSTRACT

Background: Cardiovascular health and preventative strategies are influenced by the sex of the individuals. To forecast cardiac events or detect ischemic heart disease (IHD) early, machine-learning algorithms can analyze complex patient data patterns. Early detection allows for lifestyle changes, medication management, or invasive treatments to slow disease progression and improve outcomes.

Aim: To compare and predict the differences in the primary sources of IHD burden between males and females in various age groups, geographical regions, death versus alive, and comorbidity levels.

Methods: A predictive and retrospective design was implemented in this study. Electronic health records were extracted, which were equally distributed among males and females with IHD. The dataset consisted of patients who were admitted between 2015 and 2022. Two of the eight models generated by Modeler software were implemented in this study: the Bayesian network model, which achieved the highest area under curve score (0.600), and the Chi-squared automatic interaction detection (CHAID) model, which achieved the highest overall accuracy score (57.199%).

Results: The study sample included 17,878 men and women, 58% of whom had no comorbidities and 1.7% who died. Age, the Charlson comorbidity index score, and geographical location all predicted IHD, but age was more influential. Bayesian network analysis showed that IHD odds were highest in males 40-59 and females 60-79, with the highest mortality risk in females 80-100. North and south Jordan had higher IHD rates and middle-aged males from north and middle governorates had higher IHD rates according to CHAID.

Conclusion: By using artificial intelligence, clinicians can improve patient outcomes, treatment quality, and save lives in the fight against cardiovascular illnesses. To predict IHD early, machine-learning algorithms can analyze complex patient data patterns to improve outcomes.

Keywords: ischemic heart disease, artificial intelligence, Bayesian network model, chaid model, male, female

INTRODUCTION

Coronary artery disease (CAD), also referred to as ischemic heart disease (IHD), is responsible for the majority of fatalities worldwide [1]. About 32% of all fatalities worldwide in 2022 were attributed to CAD, with an estimated 17.9 million deaths [2]. There is a widespread understanding that the health of individuals is influenced by a variety of factors, including their sex, race, ethnicity, socioeconomic status, disability, and age [3, 4].

Gender describes the socially created roles, actions, and identities of women, men, and gender-diverse people, impacted by history and culture [5]. Sex, on the other hand, refers to the biological factors that are associated with physical and physiological traits, such as hormones, sex chromosomes, and reproductive anatomy [5, 6]. Despite the significant improvement in the mortality rate of women with IHD, it continues to be the leading cause of death [7, 8]. The mortality rate and prognosis of women following acute cardiovascular events are higher, despite the fact that males have a greater incidence of cardiovascular disease [9, 10]. Furthermore, cardiovascular disease develops 7-10 years later in females than males and is the leading cause of death in women over 65 [11]. Myocardial infarctions have increased in midlife women (35 to 54 years) and decreased in similarly aged males over the past two decades, according to recent findings [12]. Women are less likely to be referred for functional testing for ischemia than males during the previous two decades, according to the European heart survey on stable angina pectoris [13]. Increased awareness of women's cardiovascular risk factors and self-awareness should aid in the prevention of cardiovascular incident [14].

The Charlson comorbidity index (CCI) is a mortality prediction method that incorporates the classification or weighting of comorbid conditions [15]. The CCI has been incorporated in research to account for comorbidities in patients with IHD [16]. In order to regulate the prevalence of other comorbid conditions, such as diabetes, chronic pulmonary disease, or cancer, the CCI could be implemented

Table 1. Sample distribution based on sex and governorates

Governorate (location)	Male	Female	Total (%)	Jordan census: n (%)*
1-Irbid, Ajloun, Jarash, and Balqa (north)	2,458	2,458	4,916 (27.5)	3,227,100 (28)
2-Amman (middle)	4,847	4,847	9,694 (54.2)	4,834,500 (42)
3-Zarqa and Mafraq (east)	941	941	1,882 (10.5)	2,310,000 (20)
4-Madaba, Karak, Tafiela, Ma'an, and Aqaba (south)	693	693	1,386 (7.8)	1,144,400 (10)
Total	8,939	8,939	17,878 (100)	11,516,000 (100)

Note. *Department of Statistics in Jordan, 2023 census; n: Number; & %: Percentage

[17]. This enables the comparison of outcomes among patients with a diverse array of comorbidities in a concise manner.

Artificial intelligence (AI) and machine learning advancements were extensively employed in the early diagnosis of high-risk conditions, such as heart disease [18]. Machine learning can be a valuable tool for predicting CAD events with heart disease symptoms and analyzing the most important clinical features and risk factors that may result in heart attacks and fatalities when it is integrated with electronic health records (EHRs) [19, 20]. Healthcare professionals can employ machine learning algorithms to evaluate clinical features and uncover obscure and hidden links and correlations among patient data [21-24]. The purpose of this study was to examine and predict differences in the leading factors of IHD burden between males and females across geographies, ages, and comorbidity, as well as mortality outcome.

METHODS

Study Design

The study employed a comparative, predictive design through the extracted data from the EHRs of patients admitted from 2015 to 2022.

Study Variables

The health data analytics department provided the following information for the patients: age, geographic location, medical diagnosis based on the international classification of disease (ICD-10), laboratory findings including high-density lipoprotein (HDL), lactate dehydrogenase (LDH), cholesterol level, fasting blood sugar (FBS), systolic blood pressure (SBP), and diastolic blood pressure (DBP). Data were extracted from multiple Excel sheets. Age, medical diagnosis, and place of residence had complete data without missing. However, a significant amount of the data regarding LDH, HDL, cholesterol, glycated hemoglobin (HbA1c), creatinine, FBS, and vital signs–including pulse oximetry-measured oxygen saturation, heart rate, SBP, and DBP–were missing. The data were merged into a single file using the SPSS software, which was subsequently sorted and cleaned.

As our aim in this paper was to compare factors that affect IHD based on the sex of the individuals using AI prediction models, we matched the number of participants from each group of governorates based on this variables (**Table 1**). This distribution is close to the typical Jordanian population distribution [25].

Data Processing

The data were analyzed for noise, inconsistency, and missing values using frequency analysis and outlier identification. Sorting, cleaning, and structuring the retrieved data resulted in the removal of a significant amount of redundant material.

Data Transformation

Using data visualization, the researchers selected the most pertinent characteristics of CAD. Additionally, the data were manipulated, analyzed, and visualized using SPSS Modeler version 18.0 [26]. This software has the capabilities of high statistical power data presentation, predictive analysis, and data management for descriptive and predictive modeling [27]. Descriptive modeling was implemented to identify the primary risk factors for cardiac disease that lead to mortality. Furthermore, predictive modeling was employed to develop the appropriate model, with an emphasis on the overall accuracy and the area under the curve (AUC).

Developing an Appropriate Model

The IBM Corporation software program SPSS Modeler was used in creating and implementing predictive models. After being processed and transformed, the data were imported for analysis. Based on the goals of the study, the type of problem, and the quality of the data, a suitable model was chosen. The selection of the best AI model is mostly based on overall accuracy and AUC [28]. In our study, out of the eight models, the Bayesian network model had the highest AUC score (0.600), followed by the Chi-squared automatic interaction detection (CHAID) model (0.598). Furthermore, the CHAID model had the highest overall accuracy score (57.199%), followed by the Bayesian network model (57.115%). Thus, we chose to analyze and interpret the data for this study using both the Bayesian network and the CHAID models (**Figure 1**).

Model	Area Under Curve	Overall Accuracy (%)
Bayesian Network 1	0.600	57.115
CHAID 1	0.598	57.199
Decision List 1	0.588	56.74
Neural Net 1	0.587	57.042
Logistic regression 1	0.587	56.746
C5 1	0.575	57.182
Quest 1	0.574	57.182
C&R Tree 1	0.574	56.74

Figure 1. The eight generated models by AI (Source: Authors' own elaboration)

Table 2. Sample characteristics (N = 17,878)

Characteristics	n	%
Sex		
Male	8,939	50.0
Female	8,939	50.0
Charlson comorbidity index score		
0	10,303	57.6
1	6,525	36.5
2	933	5.2
3	114	0.6
4	3	0.1
Dead vs. alive		
Dead	298	1.7
Alive	17,580	98.3
Age group		
18-39	2,352	13.2
40-59	6,773	37.9
60-79	7,630	42.7
80-100	1,123	6.3

Note. n: Number & %: Percentage

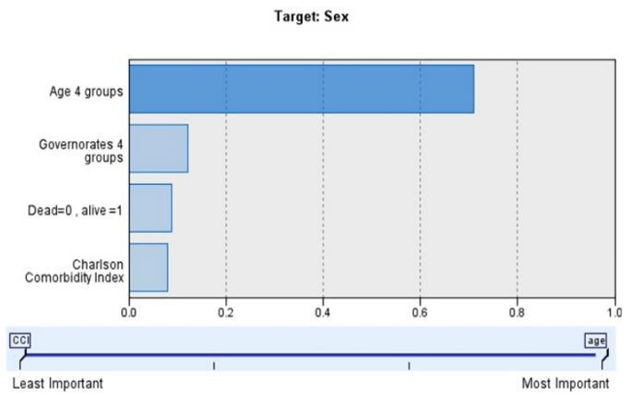

Figure 2. Predictors' importance as identified by the AI model (Source: Authors' own elaboration)

RESULT

Table 2 illustrates the characteristics of the study sample. The cohort was composed of 17,878 participants, who were equally divided between males and females. Approximately 58% of individuals do not have any comorbid conditions, while approximately 37% have a score of one in the CCI. The death status was reported for 298 individuals (1.7%) in the sample. The sample was divided into four age categories, with the youngest group (18-39 years) comprising 13.2% and the oldest group (80-100 years) comprising 6.3% of the total sample.

The Importance of the Predictors as Identified by the AI Model

The AI models identified five predictors concerning the sex of the participants, as illustrated in **Figure 2**. Age is the most important predictor, followed by CCI, death versus alive, and geographical location, as evidenced by the governorates.

The Bayesian network model demonstrates the relationships between the sex of the participants and the five predictors, as shown in **Figure 3**. A Bayesian network model is a graphics-based model that illustrates the probabilistic relationships between a set of variables [29]. The Bayesian network would depict these relationships by using directed edges (arrows) between the nodes. These arrows' strength and

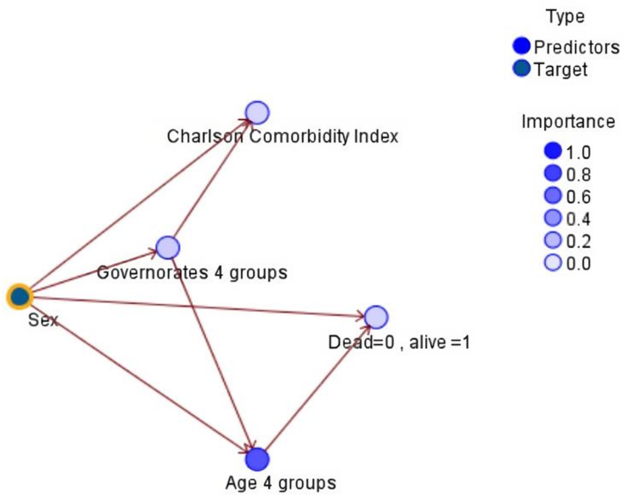

Figure 3. Bayesian network model for the study variables (Source: Authors' own elaboration)

direction are quantified through the use of conditional probabilities.

Following the Bayesian model and as illustrated in **Table 3**, the conditional probabilities of having IHD are influenced by age, with females being more likely to fall within the 60-79 age group. Nevertheless, the probabilities were highest among males aged 40 to 59. The probabilities of IHD in patients were nearly the same between males and females across various age categories according to their comorbidities. Interestingly, the AI model indicates that females aged 80 to 100 had the highest likelihood of death (0.06).

Figure 4 illustrates the decision tree for the study variables in the CHAID model. It started with the root node (males versus females) as the target outcome, represented by node 0. Age groups in nodes 1 to 4 were the predictors with the strongest relationship to the target field, as indicated by the statistical significance of the predictor (Chi-square = 459.40, $p < .001$). Although the middle age group in node 2 (40-59 years) has the only higher percentage of males than females (59%), the other three groups in nodes 1, 3, and 4 have a higher percentage of females with IHD. The north and south governorates had a higher prevalence of IHD (19%) than the middle and east of Jordan (10%), as evidenced by the split of the youngest age group into nodes 5 and 6 (Chi-square = 21.09, $p < .001$). As shown in nodes 13-16, individuals in middle age (40-59 years) from north and middle governorates were more males than females with IHD, irrespective of their CCI score (Chi-square = 13.36, $p < .001$).

DISCUSSION

The study used AI models to evaluate the variables influencing IHD among males and females, involving a balanced cohort of 17,878 participants. This balanced distribution by sex and geographic representation reflects the broader Jordanian population demographics, enhancing the generalizability of the findings. The participants were categorized into four distinct age groups, with a significant majority (nearly 80%) falling within the 40 to 79 years age bracket. This age-focused analysis is particularly relevant, given the increased prevalence of IHD in older populations. The use of AI in this context underscores its potential in identifying

Table 3. The probabilities of sex of the participants and predictor variables as determined by the Bayesian network model

	Conditional probabilities of age				Conditional probabilities of CCI						Conditional probabilities of dead vs. alive	
Governorates/female	**18-39**	**40-59**	**60-79**	**80-100**	**0**	**1**	**2**	**3**	**4**	**Age 4 groups/female**	**Alive**	**Dead**
1-North	0.25	0.34	0.34	0.07	0.53	0.39	0.07	0.01	0.00	18-39	1.00	0.00
2-Middle	0.10	0.30	0.51	0.09	0.58	0.36	0.05	0.00	0.00	40-59	0.99	0.01
3-East	0.07	0.32	0.53	0.09	0.62	0.33	0.04	0.01	0.00	60-79	0.97	0.03
4-South	0.09	0.28	0.52	0.12	0.60	0.37	0.03	0.00	0.00	80-100	0.94	0.06
Governorates/male										**Age 4 groups/male**		
North	0.19	0.47	0.31	0.03	0.50	0.40	0.08	0.01	0.00	18-39	1.00	0.00
Middle	0.10	0.40	0.45	0.04	0.61	0.34	0.04	0.00	0.00	40-59	0.99	0.01
East	0.12	0.52	0.32	0.03	0.60	0.36	0.04	0.00	0.00	60-79	0.99	0.01
South	0.08	0.56	0.32	0.03	0.60	0.36	0.04	0.00	0.00	80-100	0.97	0.03

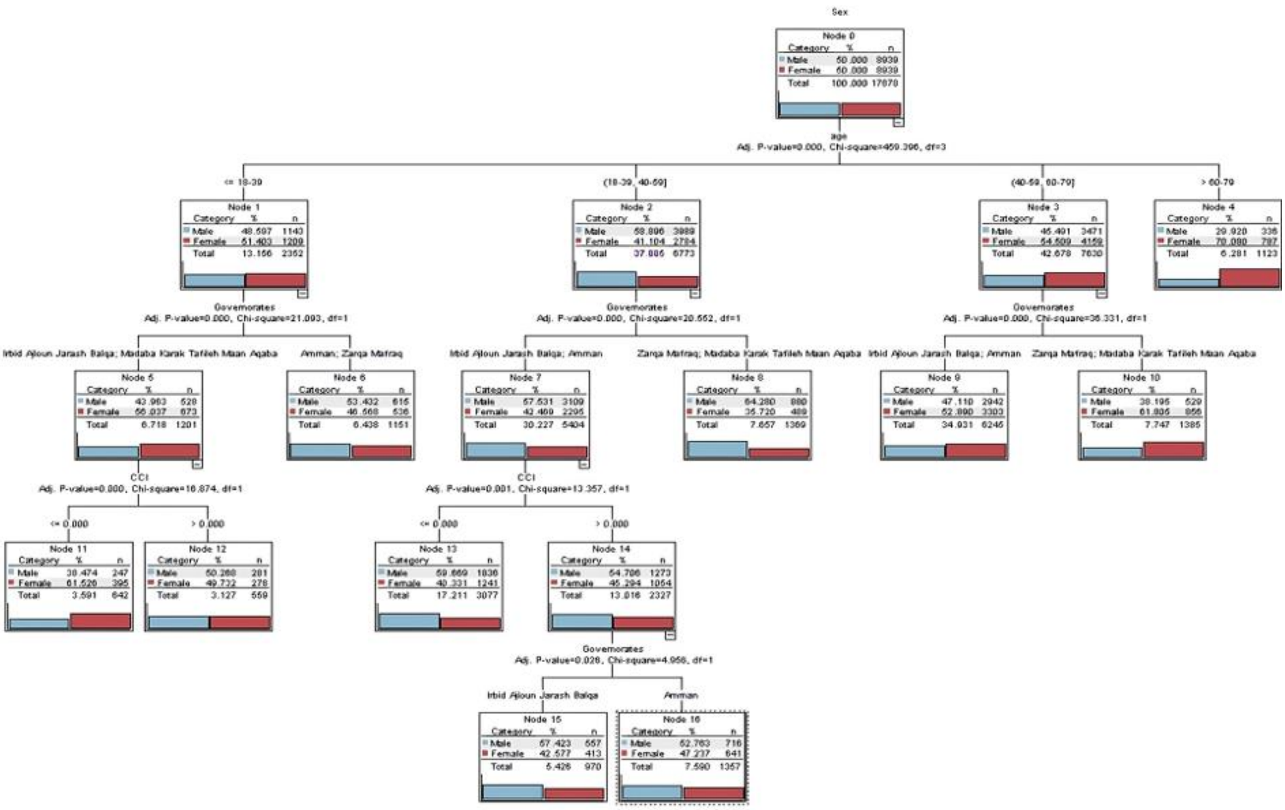

Figure 4. The CHAID model's decision tree for the study variables (Source: Authors' own elaboration)

sex-specific and age-related risk factors, providing valuable insights for targeted prevention and treatment strategies in diverse demographic settings.

In analyzing the data for this study, we employed both the Bayesian network and CHAID models, selecting these due to their robust performance metrics. The Bayesian network model was chosen for its superior AUC score, indicating a high capability to distinguish between different outcomes. On the other hand, the CHAID model was used for its highest overall accuracy score, ensuring precise and reliable predictions. By leveraging these two models, we aimed to maximize the predictive power and interpretive clarity of our analysis, allowing for a comprehensive understanding of the variables impacting the study outcomes. This dual-model approach enhances the robustness of our findings and provides a more refined insight into the data.

There is a generalized increase in the risk of developing IHD in men at an earlier age than in women [18, 30]. After menopause, the risk of IHD in women increases and is comparable to that of males [31]. In our study, the AI models identified five key predictors of IHD relative to the sex of the participants: age, CCI, mortality status, and geographical location based on governorates.

Age emerged as the most significant predictor, underscoring the well-documented association between advancing age and increased IHD risk. The age-standardized prevalence of CADs in Jordan was estimated to be 7,980 per 100,000 population in 2019 [25]. In the same year, the mortality rate from cardiovascular disease was 248 per 100,000 individuals [17]. The age-standardized prevalence, mortality, and disability-adjusted life years rates for cardiovascular diseases (CADs) decreased by 5.5%, 45.1%, and 46.7%, respectively, between 1990 and 2019 [32].

The findings from the Bayesian model present intriguing insights that both align with and challenge existing literature on IHD. Consistent with established knowledge, the results indicate that men aged 40-59 have the highest odds of IHD, reaffirming the well-documented increased risk in middle-aged men [1, 33]. However, the observation that females in the 60-79 age range are more likely to develop IHD suggests a heightened vulnerability in older women, potentially linked to post-menopausal changes and hormonal factors, which is increasingly recognized in recent studies but has historically been underemphasized.

The recorded mortality rate of about 2% in our study is less than the general mortality statistics as reported in 2022 for IHD [34]. This may be due to the relatively youthful average age of the sample in the current study (mean [M] = 58.8, standard deviation [SD] = 15.2). Nevertheless, the AI CHAID model showed that 80-100-year-old women show the highest mortality risk contradicts some traditional views that often emphasize higher mortality rates in men across age groups [32, 35]. This finding underscores the critical need to focus on elderly women, who may be at a higher risk for fatal outcomes from IHD.

The decision tree analysis of the CHAID model provides insights that both confirm and challenge the current understanding of the distribution of IHD risk across genders and age categories. The root node distinguishes between males and females, highlighting sex as a primary factor in IHD risk assessment, which is consistent with the findings in a meta-analysis [36]. Furthermore, age groups, identified as the strongest predictors, reinforce the understanding that age significantly influences IHD risk. However, the finding that the 40-59 age group (node 2) shows the highest percentage of males with IHD aligns with traditional views, affirming that middle-aged men are particularly vulnerable to IHD [37].

Conversely, the higher prevalence of females in nodes 1, 3, and 4 (covering younger and older age groups) differs from the conventional narrative that men are consistently at higher risk across all age ranges [19, 38]. This suggests that females, especially those outside the middle age bracket, may have a higher incidence of IHD than previously recognized. These results challenge the conventional male-centric approach to IHD research and emphasize the necessity of examining gender-specific factors across various age categories [39]. This comprehension calls for more inclusive and targeted prevention and intervention strategies that address the unique risk profiles of both men and women throughout their lives.

The observed higher prevalence of IHD in the north and south governorates of Jordan compared to the Middle and East regions introduces regional disparities that merit further exploration. This geographical variation suggests that environmental, socioeconomic, and healthcare access factors specific to these areas might significantly influence IHD risk [40]. Traditionally, regional disparities in IHD prevalence have been underexplored in Jordan, making these findings particularly relevant for public health planning and resource allocation.

Moreover, the data shows that middle-aged males in the north and middle governorates have a higher incidence of IHD than females, regardless of their CCI score. While it is well-documented that men generally have higher IHD rates [41, 42], this finding underscores a particularly acute risk for males in these specific regions. Alternatively, it suggests that there may be unaccounted behavioral or genetic factors at play, or that regional factors may disproportionately affect males.

Although the study possesses various strengths such as a substantial sample size, a well-balanced cohort, and the utilization of sophisticated AI models, it also has several possible limitations. A key limitation is the amount of missing data for important biochemical and physiological markers, such as LDH, HDL, cholesterol, HbA1c, creatinine, FBS, and vital signs. This absence may have limited our ability to fully assess participants' health and the risk factors for IHD. Although AI models can be effective instruments for identifying patterns in data, their effectiveness is contingent upon the data on which they are trained.

Implications

Machine-learning algorithms have the potential to substantially improve patient care and clinical decision-making for individuals with IHD. These algorithms can enable more precise and personalized risk assessments by enhancing prediction models. Additionally, the results suggest that gender and age-specific approaches to IHD prevention and treatment should be reassessed, underscoring the necessity of interventions that are customized to accommodate a variety of risk profiles. To guarantee the robustness and applicability of these sophisticated predictive models, future research should prioritize comprehensive data acquisition.

CONCLUSION

The management of IHD has the potential to be transformed by machine-learning algorithms, which offer clinicians sophisticated tools for data analysis, prediction, and decision support. In the fight against cardiovascular diseases, clinicians can improve patient outcomes, enhance the quality of care, and ultimately save lives by leveraging the power of AI. Despite a decrease in the burden rate of CADs between 1990 and 2019, IHD continues to present a significant health challenge in Jordan. In order to fully understand the precise factors that contribute to IHD in Jordan, further research is necessary. Machine-learning algorithms are capable of analyzing complex patterns in patient data to predict the likelihood of future cardiac events or identify early indicators of IHD. This early detection can lead to opportune interventions, such as lifestyle modifications, medication management, or invasive procedures, to prevent disease progression and improve outcomes.

Author contributions: MA: conceptualization, data curation, formal analysis, methodology, project administration, software, supervision, validation, visualization, writing – original draft, writing – review & editing; **SB:** conceptualization, data curation, investigation, methodology, project administration, visualization, writing – review & editing. Both authors have sufficiently contributed to the study and agreed with the results and conclusions.

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Ethical statement: The authors stated that the study was approved by the School of Nursing/University of Jordan's Scientific Research Committees. Additionally, data collection under number #MOH/REC/2022/3 was approved by the Ministry of Health's Ethics Committee. Written informed consents were obtained from the participants. By using an identification number for each record, patient information was managed in confidence.

Declaration of interest: No conflict of interest is declared by the authors.

Data sharing statement: Data supporting the findings and conclusions are available upon request from the corresponding author.

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