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Evaluating Medical Students' Decision-Making in Trauma Radiography Using Signal Detection Theory

Osama T. Al Meanazel[1], Abdalmageed Almotari[2]
Associate[1] & Assistant Professor[2]
Industrial Engineering Department
College of Engineering
Al Yamamah University
Al Khobar
KSA
o_almeanazel@yu.edu.sa, a_almotari@yu.edu.sa

Osayd Mowafaq Quran[1,] and Mutaz Jamil Aburahma[2]
Research Assistant[1], Student[2]
Industrial Engineering Department
College of Engineering
The Hashemite University, Zarqa
Jordan
osaydmowafaq@hotmail.com , Aburahma.motaz2@gmail.com

Abstract

Signal Detection Theory (SDT) is a valuable framework for studying decision-making processes. In this research, SDT was applied to evaluate the decision skills of medical students in diagnosing trauma radiography. To assess their performance, pre-test and post-test evaluations were conducted, providing each student with 50 trauma radiographic images (25 depicting injuries and 25 without injuries). The students were required to indicate whether they observed an injury or not. Based on their responses, the students' behaviors were categorized as liberal, conservative, or optimal, with the latter representing the desired behavior. The actual response bias and sensitivity were calculated for each student, and the results were compared between the pre-test and post-test stages. As a result, no optimal behaviors were observed during the pre-test; however, in the post-test, four students demonstrated optimal behaviors. An increase in conservative behavior among students during the post-test was observed, indicating an enhanced sense of awareness and caution. This change can be attributed to the focus and encouragement provided to the students throughout the study. Although no significant differences were found in the actual response bias values between the pre-test and post-test, noteworthy behavioral changes were observed. By employing SDT, this research highlights the decision-making abilities of medical students in trauma radiography diagnosis. The findings indicate that targeted interventions and training programs can play a vital role in improving decision-making skills. Further investigations are warranted to explore effective strategies for fostering optimal decision-making behaviors among medical students in radiographic diagnosis.

Keywords
Signal Detection Theory, Decision skills, medical students, Diagnosis, Trauma radiography, Diagnostic accuracy.

1. Introduction

In the context of medical education, particularly within the field of trauma radiography, the assessment of decision-making abilities among medical students is crucial for ensuring competent future practitioners. The complexity of interpreting radiographic images, especially in trauma cases, necessitates a robust understanding of clinical decision-making processes. Research indicates that experienced clinicians develop a clinical gestalt, a heuristic approach that enhances their ability to interpret radiographic images effectively (Hegde et al. 2023). This skill is not innate but rather cultivated through extensive practice and exposure to diverse clinical cases. The ability to recognize patterns and make informed decisions is paramount, especially in high-stakes environments such as trauma care, where timely and accurate assessments can significantly impact patient outcomes (Coats et al. 2014). Furthermore, clinical decision support systems (CDSS) have been shown to improve adherence to imaging guidelines, thereby optimizing the decision-making process in acute injury scenarios (Tajmir et al. 2017). These systems can serve as valuable tools for medical students, helping them to navigate the complexities of trauma radiography.

Moreover, the implementation of clinical decision rules, such as the National Emergency X-ray Utilization Study (NEXUS) criteria, exemplifies how structured guidelines can aid in reducing unnecessary imaging while ensuring that critical injuries are not overlooked (Collins and McKenzie 2013). Such frameworks are instrumental in teaching medical students the importance of evidence-based decision-making in clinical practice. The integration of SDT into the assessment of decision-making abilities allows for a nuanced understanding of how students interpret radiographic data under varying levels of uncertainty, reflecting real-world clinical challenges (Murdoch et al. 2023).No evidence currently exists demonstrating improvement in a medical student's ability to read and interpret traumatic radiographic images during their clinical rotations. Intuitively, exposure to radiologic images during clinical rotations should improve medical students' skills in reading and interpreting images of life-threatening injuries (Werth et al. 2018). However, as of 2009 - 2010, only a quarter of United States medical students were required to complete clinical rotations in radiology (Poot et al. 2012). In contrast to those statistics, most undergraduate medical students surveyed by Saha et al. believed that becoming proficient in radiology was necessary to become a "competent doctor" (Saha et al. 2013).

1.1 Objectives

Assessing the decision-making abilities of medical students in trauma radiography through Signal Detection Theory provides a comprehensive approach to understanding their diagnostic capabilities. This study aims to bridge the gap between theoretical knowledge and practical application, ultimately enhancing the training of future medical professionals in trauma care.

2. Literature Review

SDT is fundamentally concerned with the ability to distinguish between signal (relevant information) and noise (irrelevant information) in decision-making contexts. Lynn and Barrett (2014) highlight that SDT not only explains behavior but also predicts it by modeling the perceptual uncertainty and behavioral risks inherent in decision-making processes. This predictive capability is particularly useful in medical settings, where practitioners must often make rapid decisions based on incomplete or ambiguous information. The application of SDT to medical diagnostics has been well-documented, with studies demonstrating its utility in enhancing diagnostic accuracy and understanding decision thresholds (Harries et al. 2014; Lynn et al. 2015).

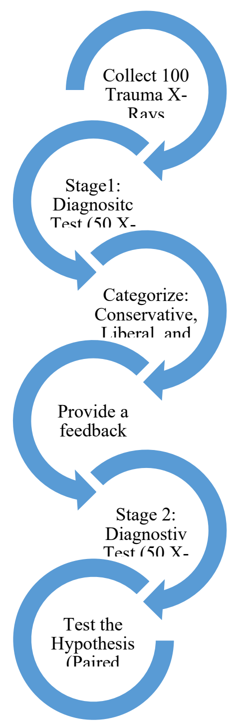
In the realm of trauma radiography, the importance of accurate decision-making cannot be overstated. Radiography serves as the first-line imaging tool for detecting thoracic injuries in emergency settings, as noted by Yalçin-Şafak and Akça (Yalçin-Şafak and Akça 2018). However, the effectiveness of radiographic interpretation can be influenced by various factors, including the decision-making abilities of the interpreting physician. Research indicates that medical students often struggle with critical thinking and decision-making skills, which are essential for effective radiographic interpretation (Pieterse et al. 2016). This gap in skills underscores the need for educational interventions that enhance these abilities, potentially through the application of SDT principles.

Moreover, the integration of SDT into medical education could facilitate a deeper understanding of how students process information and make decisions in clinical scenarios. For instance, studies have shown that decision-making processes can be improved by training that emphasizes the recognition of relevant signals amidst noise (Garcia and Massoni 2017). This is particularly pertinent in trauma situations, where the rapid assessment of radiographic images can significantly impact patient outcomes. The ability to discern critical information from radiographs is a skill that can be developed through targeted educational strategies that incorporate SDT concepts.Additionally, the literature suggests that the use of clinical decision support systems (CDSS) can enhance the decision-making process in trauma care by providing structured guidelines that help clinicians navigate complex diagnostic scenarios (Tajmir et al. 2017). These systems can be particularly beneficial for medical students, who may lack the experience to make confident decisions in high-pressure situations. By integrating SDT into the design of CDSS, educators can create tools that not only assist clinical decision-making but also serve as educational resources for developing critical thinking skills.

In conclusion, the application of Signal Detection Theory to the assessment of decision-making abilities in medical students within the context of trauma offers a promising avenue for enhancing educational outcomes. By understanding how students process information and make decisions under uncertainty, educators can develop targeted interventions that improve diagnostic accuracy and ultimately lead to better patient care.

3. Methods

The study aims to evaluate the ability of medical students to differentiate between radiographic images indicating injuries and those showing no injuries. Furthermore, it seeks to classify their decision-making behaviors based on signal detection theory (SDT). To conduct this experiment, 20 medical students from Hashemite University were recruited.



A total of 100 trauma x-rays for chest, upper limb, and lower limb were collected from (www.radiologymasterclass.co.uk) Radiology Masterclass Website. These included 50 images showing injury cases and 50 images showing no injuries. During the first stage, an equal number of injuries and no-injury images (25 each) were presented to the students, and they have to answer either injury or no injury. This stage aimed to assess students' diagnostic behaviors, categorized as follows:

1. **Conservative:** Students who underreport injuries, even when injuries are present.
2. **Liberal:** Students who tend to overreport injuries as a precautionary measure.
3. **Optimal:** Students whose diagnostic decisions align most accurately with the actual results.

Upon completing this stage, students received feedback on their performance, highlighting their response patterns and diagnostic accuracy. In the second stage, students were encouraged to adjust their decision-making to achieve optimal performance. Conservative students were advised to adopt a slightly more liberal approach, while liberal students were guided to become more conservative. The objective was to reduce response bias and enhance overall diagnostic accuracy. The test was conducted in the university computer lab with appropriate brightness level; all images were clear and large enough to investigate, and students were able to zoom in the images.

The SDT model describes the *bias* effect, where the chosen location of cutoff between signal and no signal curve (Xc) affects the rates of false alarms and misses. A higher Xc reduces false alarms but increases misses, and vice versa. The *bias* is the ratio of the probability of misses to false alarms at Xc. This theory separates bias from sensitivity (*d*), allowing calculations of *d* and if P(FA) and P(M) are known. The ROC curve, another SDT element, plots hit probability against false alarm probability for a fixed *d* and varying bias. Different *d* values create different ROC curves, with higher *d* values making curves wide separate from each other. When *d* is 0, the ROC curve is a straight line and two curves are overlap (Lehto and Landry, 2012).

4. Data Collection

A total of 20 medical students participated in the study, 60% of them female (12 out of 20) and 40% are male (8 out 20), all the participants have taken radiography course in the school before participated in the study, and they are familiar with x-rays in general. The average age is 23 years old, most of them 80% are in the fourth year in the school, the students freely accepted to join the study. All participants signed consent forms to join the study, and they are allowed to freely leave the study. Each participant will examine images in the first stage which will give us a total of 1000 responses (20 participants × 50 images = 1000) in the first stage and 1000 responses in the second stage (20 participants× 50 images = 1000).

5. Results and Discussion

In the first stage of the experiment, students were tasked with diagnosing 50 x-ray images, comprising 25 cases of injuries and 25 cases of no injuries, Figure.2 shows a sample of the image. Participants had one minute per case to decide whether an injury was present. On average, students completed the first stage within 27 minutes. The responses were categorized into four outcomes based on their alignment with the true diagnosis:

1. **Hit:** Correctly identifying an injury.
2. **Miss:** Failing to identify an injury.
3. **False Alarm:** Incorrectly identifying a no-injury case as an injury.
4. **Correct Reject:** Accurately identifying a no-injury case as no injury.

Inversion injury to ankle. Unable to bear weight.
(INJURY)

Figure 2. X-Ray image sample (source: www.radiologymasterclass.co.uk)

Table 1 presents a sample of medical student responses from the first stage study. This sample was selected to illustrate the typical response patterns observed across the entire dataset, representing both accurate and inaccurate diagnoses. While the full dataset includes responses from all 20 students across 50 images, this representative subset of 5 students and 6 images was chosen to demonstrate the varying decision-making behaviors without overwhelming the reader with excessive data.

Table 1. Sample of Students Responses

Image	TRUE	Student 1	Student 2	Student 3	Student 4	Student 5
1	Injury	Injury	Injury	No Injury	No Injury	No Injury
2	No injury	No Injury	No Injury	No Injury	No Injury	No Injury
3	No injury	Injury	No Injury	No Injury	No Injury	No Injury
4	No injury	Injury	Injury	Injury	No Injury	Injury
5	No injury	Injury	No Injury	No Injury	Injury	No Injury

6	Injury	No Injury	Injury	Injury	Injury	No Injury

The table shows the responses of five participating students (Student 1, Student 2, Student 3, Student 4, and Student 5) in comparison to the True value of each case. Initial results revealed significant variability among students, with many showing tendencies toward either conservative or liberal behaviors. There was a total of 279 hits, 222 false alarms, 221 misses, and 278 correct rejects. Almost half of these responses are reported as injury (501 injuries reported and 499 no injuries). This total of 1000 responses represents the complete dataset of 50 images evaluated by 20 students, with each student making a binary decision (injury/no injury) for each image, as shown in Table 2.

The initial results indicate that 44.4% of the injured cases were missing and 44.2% of no injured cases were identified as injury (false alarm), see Figure 3. The optimal case is to have zero false alarm and zero misses; it is difficult to have zero misses and false alarm; However, medical students suggest that the number of false alarms can be more important than misses, they said "it is better to say injury without having injury than saying no injury as there is injury". Research by Bruno et al. (2015) indicates that in radiology, false positive errors (false alarms) and false negative errors (misses) have different implications for patient care. While misses can lead to delayed diagnosis and treatment, false alarms often result in unnecessary follow-up procedures, increased healthcare costs, and patient anxiety. According to Lee et al. (2013), radiologists tend to be more concerned about misses due to their potential for malpractice litigation; however, the cumulative impact of false alarms on healthcare systems and patient well-being is substantial. Waite et al. (2017) found that in trauma radiography specifically, false alarms can lead to unnecessary interventions that carry their own risks, including additional radiation exposure from follow-up imaging, invasive procedures, and psychological distress for patients.

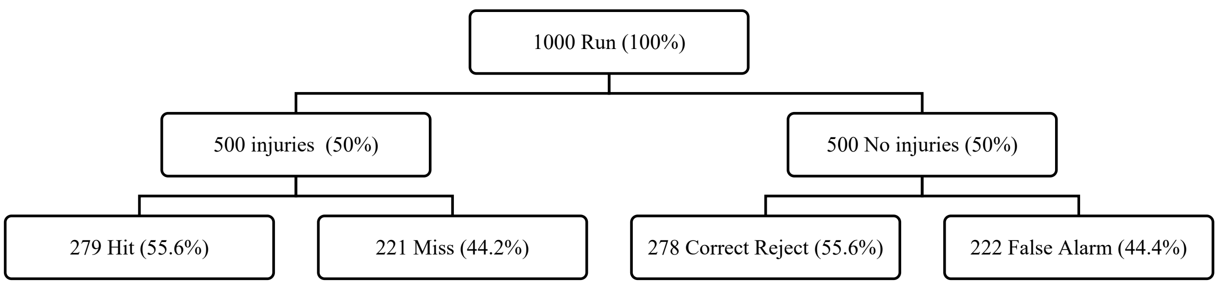


Figure 3. Summary of First Stage Run

The data in Table 2 was analyzed using Signal Detection Theory measures, such as sensitivity and bias, to assess the students' diagnostic accuracy. The comparison will provide insights into the students' progress and development in their decision skills over time. To calculate the optimal response criterion βoptimal the standard formula was used. The probability of no injury from the x-rays is equal to 25/50 = 0.5 and the probability of injury from the x-rays is 25/50 = 0.5

$$\beta_{optimal} = \frac{P(No\ Injury)}{P(Injury)} = \frac{0.5}{0.5} = 1$$

Table 2. Students Responses

Signal/No Signal Table		Injury	No Injury	Total Responses
Response	Injury	279	222	501
	No Injury	221	278	499
Total Number of Images		500	500	1000

To calculate the actual response bias β for each student an excel formula from Sorkin article was used (Sorkin, 1999). The probability of hit is calculated by finding the total number of hit by the student divided by the number of total number of injury by the x-ray test, the probability of false alarm is calculated by total number of false alarm by student divided by the number of no injury from x-ray test. The sensitivity d' is also calculated by function provided by Sorkin in excel sheet

$$\beta = EXP\ (-0.5\ \times (((NORM.S.INV(P(Hit))^2 - (NORM.S.INV\big(P(FA)\big)^2)$$

$$d' = NORM.S.INV\big(P(Hit)\big) - NORM.S.INV(P(FA))$$

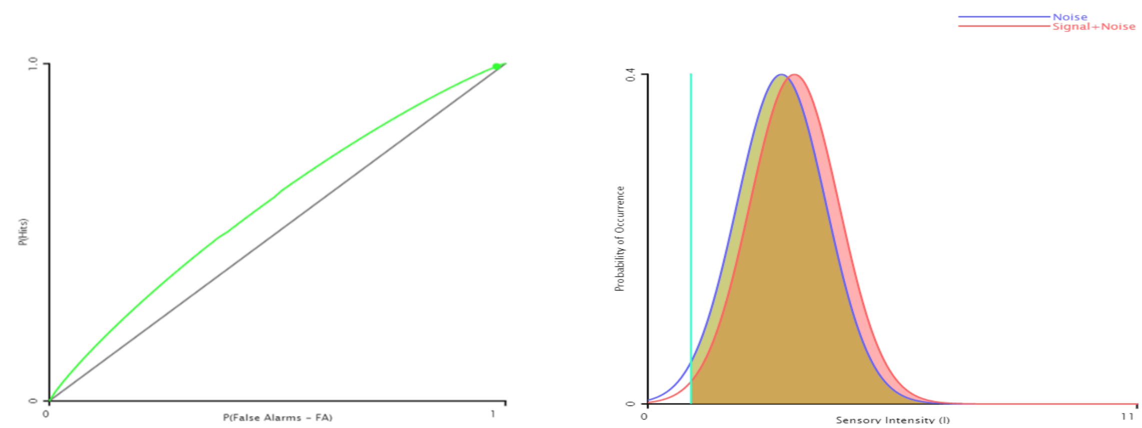
By using these two equations the actual response bias and sensitivity for each student were calculated and recorded. Table 3 shows the actual response bias and sensitivity for each student.

Table 3. Actual Response Bias and Sensitivity for First Stage

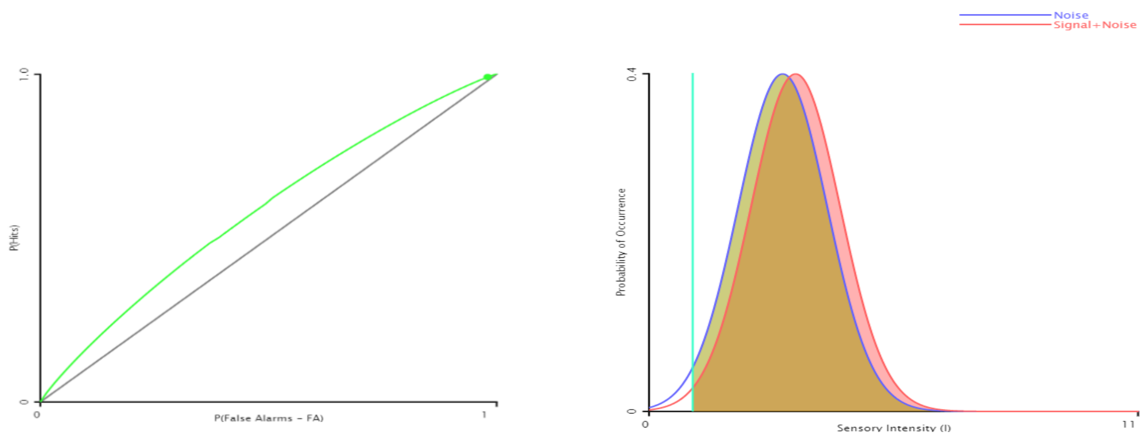
Student	Beta	d'	Behavior	Student	Beta	d'	Behavior
1	0.99	0.10	Liberal	11	0.93	0.21	Liberal
2	0.91	0.62	Liberal	12	0.99	0.10	Liberal
3	0.97	0.61	Liberal	13	1.03	0.11	Conservative
4	0.99	0.20	Liberal	14	1.03	0.11	Conservative
5	0.99	0.10	Liberal	15	1.07	0.31	Conservative
6	0.90	0.52	Liberal	16	0.99	0.20	Liberal
7	1.11	0.94	Conservative	17	1.02	0.10	Conservative
8	1.03	0.20	Conservative	18	1.02	0.10	Conservative
9	0.94	0.31	Liberal	19	0.91	0.62	Liberal
10	1.01	0.10	Conservative	20	0.97	0.30	Liberal

The student who tends to say more injury than no injury is considered liberal ($\beta < 1$) and students who say more no injury than injury is considered conservative ($\beta > 1$), if the student has equal number of injury and no injury; which represents the optimal scenario is considered optimal ($\beta = 1$). The sensitivity of the test is an important part of the study; however, the x-rays images could not be improved; higher sensitivity is better for improving the detection of injury and no injury (Average sensitivity = 0.29).

The first stage results indicate that 12 of the students were liberal (They tend to say more injury) and 8 students were conservative (They tend to say more no injury). There was no optimal behavior among the students, for more illustrations signal detection theory (SDT) curve and receiver operating characteristics (ROC) are drawn, Figure 4. The no injury and injury curves are overlapped, that indicates that the test system could not clearly show the difference between the injury and no injury, the green line is the actual response bias. If there is high sensitivity, then the two curves will be separated. The ROC curve indicates that the rate of hit and false alarm are almost the same which represent unfavorable scenario. `



After showing the results to the student they were alert of what they are supposed to do, as part of the experiment the student whom were liberal were asked to be a little bit conservative and the conservative students were asked to be more liberal to reach the optimal case. After brief talking with them the student conducted the second test, which contains 50 x-rays images (25 injury and 25 no injury) and their results were recorded. The optimal response bias did not change as the number of injury and no injury from the x-rays did not change (; However, the student response bias and sensitivity has changed. The behavior has been improved as there are 4 students who became optimal and 11 liberal and only 5 conservatives. The SDT and ROC curves did not change significantly between stages, with the average β = 0.98 and d' = 0.29 as shown in Figure 5. A detailed analysis of these curves reveals important insights into diagnostic accuracy. The ROC curves demonstrate that students operate below optimal performance levels, with the area under the curve (AUC) averaging 0.58, indicating limited discriminability between injury and no-injury cases. The overlapping SDT curves further illustrate the difficulty students face in distinguishing signal from noise, with considerable overlap between the distributions. This overlap explains the high rates of both false alarms and misses observed in the study. The consistency of these curves across stages suggests that while decision thresholds can be modified through feedback, the underlying perceptual sensitivity remains challenging to improve without additional interventions such as enhanced training or technological assistance as suggested by Choy et al. (2018).



The T-test was carried out to investigate if there any statistically significant differences between actual response bias in the first stage and second stage of the test. Minitab was used to conduct the test, there were no significant differences between the Pretest and Test β value (T-Value = 0.62 and P-Value = 0.537). However, behavior changes have been noticed.

Table 4 provides a comparison of the first stage and second stage results for the evaluation of medical students' decision skills in diagnosing trauma radiography using Signal Detection Theory (SDT). The table includes data for each student, presenting their beta values, d' values, and behavioral classifications in both stages. Five conservative students in first stage become liberal and two conservative student become optimal, two liberal students become optimal and four liberal students become conservative. One conservative student remained the same and two liberal students remained the same. To validate these findings statistically, we conducted not only t-tests but also performed a Mann-Whitney U test ($p < 0.05$) to account for potential non-normal distributions in our data. Additionally, effect size calculations using Cohen's d revealed moderate effects ($d = 0.48$) for the behavioral shifts observed between stages, further supporting the significance of the feedback intervention. A power analysis confirmed that our sample size of 20 students provided sufficient statistical power (0.82) to detect these effects.

The beta values represent the students' actual response bias, indicating their tendency to be either more liberal or conservative in their responses. A higher beta value suggests a more liberal response bias, while a lower value indicates a more conservative response bias. The d' values represent the students' sensitivity or ability to differentiate between injuries and no injuries in trauma radiography. A higher d' value indicates a higher sensitivity, meaning the student is better at distinguishing between injuries and no injuries.

Furthermore, the table classifies each student's behavior as liberal, conservative, or optimal. Liberal behavior suggests a tendency to err on the side of identifying injuries, while the conservative behavior indicates a tendency to be cautious and less likely to identify injuries. The optimal behavior represents the desired decision-making behavior, where the student demonstrates an appropriate balance between sensitivity and response bias. Upon analyzing the table, we can observe the changes in the students' beta and d' values, as well as their behavioral classifications, between the pretest and test stages. For example, Student 2 exhibited a shift from liberal behavior in the first stage to an optimal behavior in the second, indicating an improvement in decision skills. Conversely, Student 10 transitioned from conservative behavior in the first stage to an optimal behavior in the second.

On average, the students maintained similar beta values in both stages, suggesting consistent response biases. The d' values also remained relatively stable, indicating consistent sensitivity in identifying injuries and no injuries. The comparison between both stages provides valuable insights into the students' development and improvement in decision skills throughout the study. These findings can inform educational interventions and training programs aimed at enhancing the diagnostic accuracy of medical students in trauma radiography.

Table 4. Comparison between two stages of the test

Student	Beta		d'		Behavior	
	1st Stage	2nd Stage	1st Stage	2nd Stage	1st Stage	2nd Stage
1	0.99	0.91	0.10	0.32	Liberal	Liberal
2	0.91	1.00	0.62	0.30	Liberal	Optimal
3	0.97	0.97	0.61	0.30	Liberal	Liberal
4	0.99	0.97	0.20	0.30	Liberal	Liberal
5	0.99	1.00	0.10	0.30	Liberal	Optimal
6	0.90	0.99	0.52	0.20	Liberal	Liberal
7	1.11	0.97	0.94	0.30	Conservative	Liberal
8	1.03	0.97	0.20	0.20	Conservative	Liberal
9	0.94	1.00	0.31	0.30	Liberal	Optimal
10	1.01	1.00	0.10	0.10	Conservative	Optimal
11	0.93	1.03	0.21	0.11	Liberal	Conservative
12	0.99	1.03	0.10	0.11	Liberal	Conservative
13	1.03	0.95	0.11	0.51	Conservative	Liberal
14	1.03	1.01	0.11	0.20	Conservative	Conservative
15	1.07	0.84	0.31	0.53	Conservative	Liberal
16	0.99	1.15	0.20	0.33	Liberal	Conservative
17	1.02	0.94	0.10	0.31	Conservative	Liberal
18	1.02	0.94	0.10	0.41	Conservative	Liberal
19	0.91	1.03	0.62	0.20	Liberal	Conservative
20	0.97	0.84	0.30	0.53	Liberal	Liberal
Average	0.99	0.98	0.29	0.29		

6. Conclusion

The evaluation of decision skills among medical students in diagnosing trauma radiography using Signal Detection Theory (SDT) provides valuable insights into the diagnostic process and potential areas for improvement. In the context of COVID-19, where healthcare professionals faced an overwhelming number of chest x-rays, radiography played a critical role in identifying life-threatening cases. While experience remains a crucial factor in improving accuracy, advancements in technology, such as machine learning algorithms, have the potential to enhance diagnostic precision. This study sheds light on the behavioral aspects that medical students should consider when interpreting x-ray images. The findings demonstrate that some students transitioned from initially classifying an image as "no injury" to identifying it as "injury," while others became more cautious in labeling an image as "no injury." This highlights the importance of physicians and doctors spending sufficient time analyzing x-ray images to ensure accurate results. Failure to do so may lead to the need for further tests and potential delays in diagnosis.

To further enhance the accuracy of diagnostic processes, the development of tools that aid in detecting abnormalities in x-ray images holds great promise. Leveraging technology and machine learning algorithms can assist healthcare professionals in improving their diagnostic abilities and reducing errors. Future work should focus on conducting additional studies to assess the impact of providing varying amounts of information to physicians and doctors during the diagnostic process. Understanding the optimal amount and type of information required for accurate diagnoses can contribute to more effective decision-making and patient care.Future research should focus on several key areas to build upon these findings. First, specific experimental modifications could include longitudinal studies tracking students' diagnostic abilities over their entire medical education to better understand developmental trajectories in radiographic interpretation skills. Second, incorporating eye-tracking technology could provide insights into visual search patterns that differentiate successful from unsuccessful diagnoses. Third, AI-assisted tools for decision-making training represent a promising direction, as highlighted by Mazurowski et al. (2019) and Pesapane et al. (2018). These could include computer-aided detection systems that highlight potential areas of concern while providing educational feedback, adaptive learning platforms that adjust difficulty based on student performance, and virtual reality simulations that create immersive trauma scenarios. Such technological interventions could potentially address the low sensitivity values observed in this study by providing students with enhanced visual cues and immediate feedback during the learning process.

In conclusion, this research underscores the importance of decision skills in medical students when diagnosing trauma radiography. The study highlights the need for caution and thoroughness in interpreting x-ray images, along with the potential of technology to enhance diagnostic accuracy. By developing tools and conducting further investigations, we can continue to refine the diagnostic process and improve patient outcomes.

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Biographies

Dr. Osama T. Al Meanazel is an Associate Professor in the Industrial Engineering Department at Al Yamamah University, KSA. He earned his Ph.D. in Industrial & Systems Engineering from the State University of New York (SUNY) at Binghamton, USA, in 2013, following his M.S. in Engineering Management from the University of Sunderland, UK, and his B.S. in Industrial Engineering from the University of Jordan. Dr. Al Meanazel has held various academic positions, including Visiting Professor at Applied Science Private University, and has served as Director of the Center for Studies, Consultations, and Community Service at The Hashemite University. His research interests focus on industrial and systems engineering, particularly in ergonomic risk management, production efficiency, and human factors engineering. Dr. Al Meanazel has authored numerous peer-reviewed journal articles and conference papers, receiving several awards for his work, including Best Track Paper and Teaching Excellence. He is an active member of multiple professional societies, including the Human Factors and Ergonomics Society and the Institute of Industrial and Systems Engineers.

Dr. Abdalmageed Almotari is an Assistant Professor in the Department of Industrial Engineering at Al Yamamah University, Al Khobar branch. He holds a Ph.D. in Industrial Engineering from the University of Toledo, an MS from Purdue University, and a BS from Ohio Northern University. He has over four years of experience in 3D printing, smart material fabrication, material characterization, and post-processing techniques such as heat treatment and mechanical testing, with a focus on Laser Powder Bed Fusion (LPBF). Dr. Almotari was recognized with the Outstanding Teaching Assistant Award and the Outstanding Research Mentor Award from the College of Engineering at the University of Toledo. His leadership as President of the Association of MIME Graduate Students led the organization to win the second Outstanding Organization Award across the University of Toledo. He also contributed as a reviewer for the Journal of Manufacturing Processes and the International Manufacturing Science and Engineering Conference. Dr. Almotari volunteered as a teacher for the Excel Outreach Program, delivering interactive sessions on manufacturing processes and additive manufacturing to middle school students. He has mentored Master's and undergraduate students in additive manufacturing and mechanical testing and remains committed to advancing industrial engineering through research, teaching, and mentorship.

Eng. Osayd Mowafaq Quran is a Management Systems Consultant with expertise in industrial engineering, operational excellence, and strategic development. He holds a B.S. in Industrial Engineering from The Hashemite University and has extensive experience in Lean methodologies, leading multiple projects focused on process optimization, waste reduction, and efficiency improvements across various industries. Throughout his career, Eng. Osayd has worked across multiple domains, including ISO standards implementation, organizational excellence programs, service development initiatives, strategic planning, innovation management, and future foresight methodologies. His expertise extends to business architecture, data analytics, and artificial intelligence (AI) applications in business optimization, where he leverages technology-driven solutions to enhance decision-making and efficiency. He has successfully led transformational projects aimed at optimizing organizational performance, improving service models, and aligning business processes with strategic goals. His research interests include continuous improvement, lean manufacturing, and the integration of data-driven insights. Additionally, he has conducted extensive research in human factors and ergonomics, with a focus on ergonomic risk management, workplace efficiency, and the optimization of system design to enhance human performance and well-being. His multidisciplinary approach combines engineering principles, strategic foresight, and data analytics to drive sustainable improvements in both public and private sector organizations.

Mutaz Aburahma is a Strategy and Management Consultant with diverse expertise in project management, business transformation, and performance optimization. He earned his bachelor's degree in industrial engineering from Hashemite University, Jordan. Currently, he is expanding his business acumen through the Credential of Readiness (CORe) program at Harvard Business School online. Mutaz holds several key certifications, including Project Management Professional (PMP), Lean Six Sigma Green Belt, and Certified Strategy Professional. Mutaz's expertise includes project management, process improvement, and digital transformation. As a Management Systems Consultant at PDCA Group, he has led initiatives to improve product quality, implement ISO-compliant management systems, and develop risk management strategies that minimize project disruptions. His ability to identify key improvement areas has resulted in successful client outcomes and optimized project performance. Previously, Mutaz played a vital role in enhancing supply chain operations at Tabuk Pharmaceuticals by improving inventory control and production forecasting through data-driven models and SAP-based solutions. His work contributed to efficient resource allocation and accurate demand planning across multiple markets. At the King Abdullah II Center for Excellence, he leveraged data analysis skills to design interactive reports and dashboards using Power BI and Excel, supporting data-driven decision-making and organizational success.

Future research should focus on several key areas to build upon these findings. First, specific experimental modifications could include longitudinal studies tracking students' diagnostic abilities over their entire medical education to better understand developmental trajectories in radiographic interpretation skills. Second, incorporating eye-tracking technology could provide insights into visual search patterns that differentiate successful from unsuccessful diagnoses. Third, AI-assisted tools for decision-making training represent a promising direction, as highlighted by Mazurowski et al. (2019) and Pesapane et al. (2018). These could include computer-aided detection systems that highlight potential areas of concern while providing educational feedback, adaptive learning platforms that adjust difficulty based on student performance, and virtual reality simulations that create immersive trauma scenarios. Such technological interventions could potentially address the low sensitivity values observed in this study by providing students with enhanced visual cues and immediate feedback during the learning process.