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Perceived Fairness of Algorithm Driven High Stakes Examinations The Role of Statistical Equivalence System Transparency and Explanation in Shaping Trust Legitimacy and Acceptance

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Research Article

Keywords: Algorithmic Legitimacy, Perceived Fairness, Trust in AI Systems, Computerized Examinations, SEM–ANN Analysis, Explainable AI

Posted Date: July 2nd, 2026

DOI: https://doi.org/10.21203/rs.3.rs-9751723/v1

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Additional Declarations: No competing interests reported.

Abstract

The increasing adoption of algorithm-driven systems in high-stakes examinations has raised critical concerns regarding fairness, trust, and acceptance. While computerized assessment systems ensure statistical equivalence across multiple test forms, students may still question their fairness due to a limited understanding of the underlying processes. This study aims to examine how system-level factors influence students' perceptions of fairness and how these perceptions shape trust, algorithmic legitimacy, and acceptance of computerized examination systems. Using algorithmic fairness theory, procedural justice, and legitimacy theory, the study proposes a conceptual model that integrates statistical equivalence, system transparency, algorithmic opacity, and item bank exposure as antecedents of perceived fairness, which in turn influences trust, legitimacy, and acceptance. The moderate role of explanation is also examined. A quantitative research design was employed using survey data collected from 502 students with experience in computerized examinations. The data were analyzed using a hybrid SEM–ANN approach to understand both linear and non-linear relationships. SEM results reveal that statistical equivalence, item bank exposure, and algorithmic opacity significantly influence perceived fairness, while fairness and trust strongly determine algorithmic legitimacy and acceptance. Notably, transparency and moderation effects were not significant. ANN findings further highlight that explanation clarity and perceived fairness are the most influential predictors of both legitimacy and acceptance. The study contributes by bridging the gap between technical fairness and perceived fairness and demonstrating that algorithmic legitimacy is the strongest driver of acceptance. Practically, the findings emphasize the importance of clear explanation, user familiarity, and trust-building mechanisms in designing fair and acceptable computerized assessment systems.

1. Introduction

The rapid advancement of artificial intelligence (AI) and algorithmic decision-making (ADM) systems has fundamentally transformed decision processes across high-stakes domains, including education, healthcare, finance, and public governance. In educational contexts, particularly in large-scale standardized testing and national examinations, computerized assessment systems increasingly rely on algorithm-driven mechanisms such as automated item selection, adaptive testing, and psychometric equating. These systems promise efficiency, scalability, and consistency in evaluation, enabling institutions to assess large populations using standardized metrics. However, their growing adoption has simultaneously intensified concerns regarding fairness, transparency, and trust, especially when decisions have significant consequences for individuals' academic and professional trajectories (Grgic-Hlaca et al., 2018; D Shin & Park, 2019).

Algorithmic systems in high-stakes examinations operate through complex computational processes, including item bank generation, statistical calibration, and equating procedures that ensure comparability across multiple test forms. From a technical perspective, statistical equivalence is a fundamental requirement to guarantee that different exam versions yield comparable results. However, emerging evidence suggests that statistical fairness alone is insufficient to ensure users' acceptance of

such systems. Instead, individuals evaluate algorithmic decisions not only based on outcomes but also on the perceived fairness of the process, including how decisions are made, explained, and justified (Newman et al., 2020; Szafran & Bach, 2024). This distinction highlights a critical tension between objective fairness (psychometric validity) and subjective fairness (perceived justice).

The concept of fairness in algorithmic decision-making is inherently multidimensional, encompassing distributive, procedural, and interactional dimensions. While distributive fairness refers to the perceived fairness of outcomes, procedural fairness focuses on the transparency and consistency of decision processes, and interactional fairness relates to the quality of communication and explanation provided to users(Brockner et al., 2000; Juijn et al., 2023). In algorithm-driven environments, procedural and interactional fairness become particularly salient, as users often lack visibility into how decisions are generated and evaluated. Consequently, the perceived opacity of algorithmic systems—often described as “black boxes”—can undermine fairness perceptions and reduce confidence in outcomes (L. Zhao et al., 2025).

A key concern that is arising from this context is the effect that transparency and explanation have on user impressions. Transparency is the degree to which an algorithmic system reveals its inner workings; that is, its logic and decision rules, while explanation means providing understandable reasons for particular outcomes. Studies highlight the impact of transparency and tailored explanations on perceived system fairness. According to recent studies, these two attributes lead to greater trust and acceptance of the system. However, these effects are not direct. When an explanation is excessive or too complex, it can increase cognitive load and lead to confusion, skepticism, and reduced trust. This is sometimes referred to as the “transparency paradox”(Kizilcec, 2016; Ngo, 2025). These findings indicate that there may be an optimal level of transparency that varies with user characteristics, task complexity, and context.

In addition to transparency, the opacity of algorithms is an important factor influencing the response of users. Users feel uncertain and distrustful towards the system, especially in critical situations, when the latter is opaque or incomprehensible (Y. Zhao et al., 2024). When things are difficult to see through, people tend to shortcut reason to justify their behaviour rather than solving the issue fairly. This impact is further highlighted among consumers with high algorithmic literacy. Indeed, such consumers are conscious of the limitations of algorithms as well as the dangers in algorithmic decisions (Moon et al., 2025; D Shin et al., 2022). The idea of trust in algorithmic systems is related to fairness perceptions. A major mechanism connecting system attributes to user acceptance. Trust refers to the user’s confidence in the dependability, precision, and authenticity of algorithmic decision-making. According to research, a variety of technical influences, such as the technology’s performance or consistency, along with a variety of relational influences like transparency (or explainability), explanation/student, and perceived fairness are important (Park & Young Yoon, 2025). In other words, people usually do not trust algorithmic systems. Instead, it is something people construct via the system and our design. In high-stakes examinations, where consequences may determine the fate of an individual, trust is an important factor influencing system acceptance and legitimacy (Choung et al., 2025; Hunsicker et al., 2026).

Recently, algorithmic legitimacy which is more than trust is growing in popularity. Legitimacy refers to the perception of a system by the audience as appropriate and acceptable and justified in its social and institutional context (Hillo et al., 2025; Schilke & Reimann, 2026). Legitimacy differs from trust since it does not merely refer to personal confidence but entails a judgment about whether a system deserves to be used. These four factors determine the algorithmic legitimacy: fairness, transparency, accountability and their normative alignment. Legitimacy is important to win the public confidence and institutional credibility of high-stakes exams. Despite being advanced considerably in the literature on algorithmic fairness, transparency and trust, much remains missing. To begin with, prior research has generally focused on algorithmic decisions, rather than the educational assessment type system, where scores are derived from psychometric equating and item banks (Conijn et al., 2023; Song et al., 2025). The technical fairness i.e. statistical equivalence and perceptual fairness i.e. user judgment are disintegrating. Thus, we have a hazy picture of how end-users evaluate algorithmic systems (Zehlike et al., 2025). Moreover, previous studies have looked at fairness and trust in a separate context. However, fewer studies have looked at the impact of fairness and trust on the legitimacy and acceptance of algorithms in critical environments (Choi & Chao, 2026)

In order to fill these gaps, the present study proposes a comprehensive model with system characteristics, psychological mechanisms, and outcomes in computerized high-stakes examinations as shown in Fig. 1. In particular, it refers to the extent to which subjects assigned to comparable assessment positions can be regarded as statistically equivalent. The mechanisms are also associated with algorithmic legitimacy and acceptance, which emerges as an important user evaluation outcome. Besides, the study investigates whether explanation and result logic clarity moderate the relation between algorithmic opaqueness and negative perceptions given better communication of vague algorithms may enhance users' understanding.

2. Literature Review and Theoretical Background

2.1 Algorithmic Decision-Making and Institutional Legitimacy

Algorithmic decision-making (ADM) is increasingly altering how institutions function by ceding authority from human actors to machines. AI systems have become ubiquitous in many fields from government to hiring and finance to education, they are making decisions about the allocation of opportunities and distribution of resources. Though ADM systems have strong efficiencies, scalability, and consistency that covers a breadth of issues, its use in high-stake decisions invokes basic issues of institutional legitimacy. Legitimacy is the extent to which decisions and the related processes are perceived as appropriate, acceptable and, in line with the norms and expectations of society. Legitimacy is commonly thought to have three different dimensions – input, throughput and output. The concept of input legitimacy pertains to the involvement and representation of the affected public in decision-making processes and legitimacy during the process. Output legitimacy relates to effective policy outcomes that

are to the liking of the affected public. All of them have been influential in the design of government forms since the downfall of the post-war settlement system (Grimmelikhuijsen, 2023). Algorithmic systems pose challenges to all three dimensions at once. They lessen human involvement, add technical complexity, and often obscure the logic of decisions, making it harder to hold anyone accountable and limiting users' ability to assess or object to decisions(Hillo et al., 2025; D Shin & Park, 2019). Furthermore, ADM systems are complex, opaque and interdependent by nature which limits the understanding of users about how decision making. A lack of understanding about how such programs work creates risks of legitimacy for the decisions made by algorithms since people might consider them as hard to understand, query, or believe. A high-stakes context such as an assessment in an educational setting makes it more important, as illegitimacy can damage individual acceptance and institutional credibility.

2.2 Perceived Fairness in Algorithmic Decision-Making

Perceived fairness refers to how fair individuals believe an algorithmic system is. According to theories of organizational justice, fairness consists of a distributional (justice of outcomes), procedural (justice of the processes that lead to outcomes), and interactional (respectfulness of the process) (Brockner & Wiesenfeld, 2013; LePine et al., 2000). The degree of fairness of outcomes is called Distributive fairness. The fairness of processes that were adopted to reach the outcomes is called Procedural fairness. The fairness of communication and explanation is known Interactional fairness. Procedural and interactional fairness are especially important in algorithmic contexts because users often cannot see inside decision making. When things are not clear and the explanation is also missing, the outcome is valid but does not happen – just because the person observes it that way. A growing number of studies show that people view algorithm decisions as less fair than human ones when the rationale behind them is not understandable (Newman et al., 2020; Szafran & Bach, 2024). In high-stakes contexts, users are more reactive to issues of injustice, so the effect is stronger. Crucially, fairness in algorithmic systems is not something that is purely technical. When computational approaches seek to guarantee fairness with respect to some statistical criterion, we must often choose between competing definitions of fairness (Grgić-Hlača et al., 2022; Zehlike et al., 2025). Hence, fairness is seen as a socio-technical construct which is shaped by legal, ethical, and contextual factors. The necessity to combine technical fairness (for instance, statistical parity) and perceptual fairness (user assessments) is emphasized in this case, especially in the context of education assessment.

2.3 Trust and Public Perception of Algorithmic Systems

Trust significantly shapes how people embrace algorithmic decision-making systems, impacting their decisions. Although algorithms are perceived as being objective and driven by data, there is evidence that complexity subverts this view. Individuals may recognize the algorithms' efficiencies as well as their reliability but may still be skeptical about their choices, especially when it comes to high-stakes scenarios (Moon et al., 2025). The trust in algorithmic systems vary depending on technical and relational issues. Technical factors include the accuracy, consistency, and reliability of AI in managing tasks, while relational factors include the quality of transparency and fairness of AI, as well as the quality

of explanation provided to users. (Taylor et al., 2023; Park & Yoon, 2025) Among these, perceived fairness has been identified as an important antecedent of trust that is hypothesized to provide users with a psychological mechanism to evaluate the system. Moreover, user trust in ADM systems is not only shaped by the availability of information but also by the sense of inclusion and recognition. Decisions made by algorithms frequently do not allow for interaction, feedback or justification, which are essential elements of procedural justice. Consequently, even the most accurate systems can produce trust deficits when users perceive exclusion from the decision-making process (Choung et al., 2025). In high-stakes exams, which brings important consequences to individuals, trust is a crucial determinant of perceived legitimacy and behavioral acceptance.

2.4 Algorithmic Transparency and Explainability

Transparency and explainability are often proposed as the key mechanisms to tackle fairness, trust and legitimacy issues related to ADM systems. Transparency refers to the extent to which a system reveals information about its structure, logic, and decision-making capabilities, while explainability is concerned with providing understandable justifications for a particular outcome (Grimmelikhuijsen, 2023; Sullivan & Weger, 2025) Grimmelikhuijsen. Research shows that transparency can improve the perception of fairness, reliability, and acceptance of algorithmic systems (Jantzen et al., 2025). Transparency helps users to assess whether the algorithmic results follow logically and are consistent by making the decision-making processes visible. Likewise, an explanation aids users in understanding decisions, decreasing uncertainty and increasing the perceived control of users. Nonetheless, the association between clarity and user behaviour is complicated and context-sensitive. Excessive transparency or excessive detail may cause information overload and distrust among users, or the ‘transparency paradox’ (Kizilcec, 2016; Ngo, 2025). This implies that transparency has to be designed well to match a user’s cognitive abilities and informational needs. Effective explanation of scoring processes and statistical equivalence mechanisms assumes great importance in high-stakes testing contexts. When technical validity differs from perception, more transparent accessibility explanations can lead to enhancements in fairness and trust.

2.5 Algorithmic Systems as Social and Institutional Actors

In recent years, scholars have gone from seeing algorithms as technical artefacts to also viewing them as social and institutional actors that in some respects shape social relations, opportunities, and power. Algorithmic systems organize social reality by classifying people and assigning them to categories, which can determine access to resources (Fourcade & Healy 2017; Chen et al. 2024).

Through classification and prediction processes, algorithmic systems can strengthen existing inequalities while generating new forms of exclusion. For instance, data-driven models can reproduce bias that may potentially affect a particular segment due to repeated historical data in their training. Moreover algorithmic systems may produce novel classifications that have no evident social meaning, making it more complicated for users to understand and evaluate decisions. In essence, algorithmic systems are responsible for shaping what gets tested and evaluated and thus which students progress

academically. Due to the power they wield, it is vital that decisions must be seen to be fair, trustworthy and legitimate. Educational institutions may face opposition, dismissal and confidence loss from stakeholders if their legitimacy is not accepted.

Although algorithmic systems have been widely researched, there are many gaps in fairness, trust, and transparency. To begin with, in existing studies fairness is sometimes seen as a technical property and sometimes as a subjective perception. This separation fails to appreciate the interdependence of statistical validity and user perception, especially where both are necessary. Another issue is that most of the literature is about ADM applications in general, while less attention has been given to high-stakes computerized examination systems which must be psychometrically validated and socially accepted (Conijn et al., 2023)). Third, although fairness and trustworthiness are often studied, there is less research done on the interaction of the two and their effect on algorithmic legitimacy and acceptance. The research on algorithmic fairness has not formally acknowledged the notion of statistical equivalence, a central concept in educational measurement. The importance of the gap is that statistical equivalence is a key mechanism through which the technical fairness of a system is achieved, but not necessarily perceived or understood by users.

Figure 1. Proposed Conceptual Research of the Study

3. Hypothesis Development

Figure 2 illustrates the relationship among the key variables in this study. Based on this conceptual framework, the development of the hypotheses is discussed in this section.

3.1 System-Level Antecedents and Perceived Fairness

In environments where algorithms make decisions, users' assessments of fairness are highly influenced by what they perceive as the decision-making process, rather than the decision itself. The term 'statistical equivalence' in high-stakes computer-based testing refers to the essential technical mechanism that ensures comparable test forms which meet scoring standards. Through the lens of psychometrics, it is ensured that there is and will be no subjective bias against any examinee. Appraisal of fairness based on mere technical properties has not been the usage pattern as per previous studies, but rather a subjective interpretation of the process (Wang et al., 2020; Szafran & Bach, 2024). When a user feels that the alternative exam forms were comparable in the same manner and similar standards were utilized to evaluate them, it will be fair. On the contrary, uncertainty regarding equivalence can create perceptions of inequality and stereotypes. As a result, equivalence of statistics will positively influence fairness. Simultaneously, the transparency of the system is essential here in shaping fairness perceptions. Transparency allows users to see how decisions are made, eliminating uncertainty and promoting confidence in the process. Multiple studies have found that algorithmic transparency is a significant contributor to fair and acceptable perceptions (Grimmelikhuijsen, 2023; Jantzen et al., 2025). On the contrary, lack of visibility restrict the users from reviewing decision logic, leading to suspicion and

unfairness. When it comes to computerized examinations, student perceptions of justice are primarily influenced by their knowledge of the selection of items and scoring and evaluation procedures. A significant barrier to fairness is the perception of algorithmic opacity rather than transparency. When systems are opaque or incomprehensible, users cannot see whether decisions have been made consistently or fairly. People don't often understand facial expressions, which causes them to rely on heuristic judgments, which negatively bias fairness perceptions (Zhao et al., 2024). Studies show that opacity is often linked with distrust and perceived unfairness, particularly in high-stakes contexts where outcomes matter greatly (Chen et al., 2024). Hence, greater perceived opacity is expected to lessen perceived fairness. Furthermore, users' past experience of item-bank-based examinations may impact their understanding and evaluation of computerized assessment systems. Being acquainted with such systems can reduce uncertainty and enhance users' ability to grasp the disparity between examination forms. People who are relatively more exposed are likely to understand that variation in questions does not necessarily lead to unfairness, thereby enhancing fairness perceptions (Conijn et al. 2023). On the contrary, lack of exposure to the system may result in misinterpretation and skepticism. It is thus expected that item bank exposure will enhance perceived fairness.

Based on these arguments, the following hypotheses are proposed:

H1

Statistical equivalence positively influences perceived fairness.

H2

System transparency positively influences perceived fairness.

H3

Algorithmic opacity negatively influences perceived fairness.

H4

Item bank exposure positively influences perceived fairness.

3.2 Perceived Fairness and Trust in Algorithmic Systems

Perceived fairness is widely considered a key antecedent of trust in decision-making systems. The procedural justice theory refers to a theory that states that individuals place more trust on a system which is fair, consistent, and unbiased (Colquitt & Rodell, 2011). System integrity and reliability are perceived by users in terms of their fairness. This might be a cognitive or emotional mechanism. The availing users are more willing to accept the decision-making process even if those experiences are not completely transparent. Multiple empirical studies establish that fairness perceptions and trust in algorithms are positively related. One study finds that fairness perceptions can enhance trust by

lowering uncertainty and increasing perceived system validity (Taylor et al., 2023; Park & Yoon, 2025). In high-stakes exams where algorithms could determine the fates of students, fairness is essential for trust. If students feel the examination system is unfair, they will not trust the results, no matter how technically correct they are. In addition, fairness perceptions can lessen the negative effects of algorithmic opacity. When systems are complicated or incomprehensible, however, perceptions of fairness can satisfy the psychological requirement for trust, allowing users to accept outcomes despite a lack of transparency. In this light, fairness can work as a mechanism of mediating system characteristics and trust. Accordingly, the following hypothesis is proposed:

H5

Perceived fairness positively influences trust in the assessment system.

3.3 Perceived Fairness, Trust, and Algorithmic Legitimacy

In addition to trust, perceived fairness plays a significant role in the construction of algorithmic legitimacy, which refers to the appropriateness of the use of a system. Legitimacy consists not only of trust in a specific actor but also of overall evaluations about the acceptability of using a system in decisions. (Suchman, 1995; Hillo et al., 2025). When it comes to high-stakes tests, authenticity is vital for institutional credibility and public acceptance. Fairness is the primary criterion to judge legitimacy According to Brockner et al. (2000), the legitimacy of systems relied upon to determine outcomes is enhanced if the systems are deemed fair. Social equity refers to an approach designed to ensure that practices lead to socially acceptable outcomes through fairness considerations. In algorithmic contexts, fairness communicates that decisions are made in a socially acceptable manner, which is essential for achieving user acceptance. On the other hand, perceived unfairness can undermine legitimacy, even if the system is technically correct. Apart from Fairness, Trust is another important mechanism through which legitimacy is established. Confidence in a system's competence, reliability, and accuracy can foster trust. This, in turn, enhances perceptions of appropriateness and acceptability. According to studies, the legitimacy of a system is enhanced by trust as they reinforce the users' acceptance of authority and system outcomes (Choung et al., 2025; Schilke & Reimann, 2026). Accordingly, trust acts as a bridge between the perceptions and evaluations of fairness and legitimacy. Based on these arguments, the following hypotheses are proposed:

H6

Perceived fairness positively influences algorithmic legitimacy.

H7

Trust in the assessment system positively influences algorithmic legitimacy.

3.4 Algorithmic Legitimacy and User Acceptance

The algorithmic legitimacy plays an important role in the behavioral and attitudinal responses of users. Acceptance refers to whether users intend to use, support and rely on algorithmic systems in the future. Including acceptance in high-stakes situations is a prerequisite for effectively implementing and sustaining algorithmic systems. As legitimacy offers a normative justification for using the system, it plays a central role in acceptance. When people believe a system is legitimate, they are more likely to accept its decisions and continue using it even when the outcomes are unfavourable. If it is perceived as illegitimate system then, such a systems will be resisted and rejected (Hillo et al., 2025). Legitimacy may encourage confidence, which may cause acceptance. Increased trust can lower perceived risk and uncertainty, which in turn enhances users' willingness to rely on the outcomes of the system. Research shows that trust can directly predict acceptance of algorithmic systems, particularly if users do not fully understand how they work (Park & Yoon, 2025). In high-stakes tests, trust may thus play the role of a mediator and also a direct predictor of acceptance. Based on this, the hypotheses are:

H8

Algorithmic legitimacy positively influences acceptance of the assessment system.

H9

Trust in the assessment system positively influences acceptance.

3.5 Moderating Role of Explanation

Transparency provides information about how the system works, whereas explanation provides the context of how the decision was made. Clarifications have been recognized as an important driver of fairness perceptions within decision-making contexts, especially algorithmic ones (Sullivan & Weger, 2025). By clarifying why decisions were made, explanations minimize uncertainty and strengthen users' ability to assess system behaviour. Crucially, explanation may strengthen the link between transparency and perceived fairness. Adding clear explanations to transparency can help users interpret system information, which ultimately leads to stronger fairness perceptions. On the other hand, if users do not have the capacity to handle and understand the technical information, disclosure on its own may be inadequate. This interaction exemplifies that explanation is a boundary condition that enhances the efficacy of transparency. Empirical studies show that given explanations moderate algorithm evaluation, as users will evaluate the algorithm more positively when a user is given a certain level of explanation, especially in complex and high-stakes contexts (Jantzen et al., 2025; Ngo, 2025). Responses with regard to scoring process, items selection process and statistical equivalence in computerized examinations assist bridging the gap between technicalities and usability.

Accordingly, the following hypothesis is proposed:

H10

Explanation positively moderates the relationship between system transparency and perceived fairness, such that the relationship is stronger when explanation is high.

4. Methodology

4.1 Research Design

This study employs a quantitative cross-sectional study that investigates students' perceptions of fairness, trust, legitimacy and acceptance of an algorithmic-driven high-stakes examination system. In view of the complexities of relationships among system-level characteristics, psychological mechanisms and behaviour outcomes, a hybrid analytical lever of SEM-ANN are used as shown in Fig. 3. SEM is utilized to evaluate the theoretical model and causal relationships since it allows the simultaneous estimation of multiple interrelationships among the latent constructs. It also proves effective in validating the measurement and structural model (Hair Jr et al., 2021; Soomro et al., 2024). Nevertheless, SEM works on the premise of linear relationships, possibly missing out on interactions that are non-linear and complex. As a result, ANN is used as a complementary technique to increase the predictive accuracy and reveal the non-linear pattern in the data (Soomro et al., 2025). Recent studies on behavioral aspects have suggested integrating SEM with ANN to enhance their explanatory and predictive potency. The process of research services consists of instrument development, data collection, validation of measurement, testing of structural model, and predictive analysis.

4.2 Population and Sample

The population of this study is in relation to students who have experience in giving computerized high-stakes examinations; item-bank-based test forms; and algorithm-based evaluation systems. A purposive sampling technique which is a non-probability sampling technique was utilized to have respondents that have the required information on computerized assessment. A full of 502 valid responses were collected and analysed. For both SEM and ANN analysis, this sample size is deemed sufficient. (Hair et al. (2012) states that SEM calls for a minimum sample size which depends on the complexity of the model. Also, samples above 300 are generally referred to as strong samples. In similar ways, ANN models rely on extensive data to enhance its training prediction. The participants selected for the study were picked from different academic levels, disciplines, and levels of functionality with computerized examinations to ensure diversity.

4.3 Instrument Development

Data was collected using a structured questionnaire developed based on established literature and adapted to the context of algorithm-driven examinations (Complete questionnaire is available in Appendix A). The instrument consists of three main sections:

1. Demographic Information: Includes gender, age, academic level, field of study, and experience with computerized exams.
2. Experience with Computerized Exams: Measures students' familiarity with algorithm-based testing environments.
3. Main Survey Constructs: Measures the study variables using multi-item scales.
All items were measured using a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). The constructs included:

- Statistical Equivalence (SE)
- System Transparency (ST)
- Algorithmic Opacity (AO)
- Item Bank Exposure (IBE)
- Perceived Fairness (PF)
- Trust in Assessment System (TR)
- Algorithmic Legitimacy (AL)
- Acceptance (ACC)
- Explanation (EXP)

The measurement items were adapted from prior studies on algorithmic fairness, trust, transparency, and technology acceptance, ensuring content validity and theoretical grounding (Grimmelikhuijsen, 2023; D Shin et al., 2022).

4.4 Data Collection Procedure

The online survey method was utilized to conduct a survey. The sampling frame comprised learners having experience with computerized examinations spaced out. Participation was voluntary and the respondents were well-informed of the study's aim. Confidentiality and anonymity were assured. Quality checks were performed on responses for completeness and consistency. The final data set contains 502 valid observations after excluding incomplete responses and outliers.

4.5 Data Analysis Strategy

The data analysis was conducted in two main stages:

Stage 1: Structural Equation Modeling (SEM): SEM analysis was performed using SmartPLS/AMOS to evaluate both the measurement and structural models.

Measurement Model Assessment:

- Indicator reliability (factor loadings > 0.70)
- Internal consistency (Cronbach's alpha, Composite Reliability)
- Convergent validity (Average Variance Extracted, AVE > 0.50)

- Discriminant validity (HTMT criterion)

Structural Model Assessment:

- Path coefficients and significance (bootstrapping)
- Coefficient of determination (R^2)
- Effect size (f^2)
- Predictive relevance (Q^2)

SEM is particularly suitable for testing theoretical relationships among latent constructs and validating the conceptual model (Hair et al., 2021).

Stage 2: Artificial Neural Network (ANN): Following SEM analysis, ANN was applied to validate and enhance predictive performance. ANN is capable of capturing complex, non-linear relationships that may not be detected by SEM.

The ANN analysis involved:

- Input layer: significant predictors from SEM
- Hidden layers: optimized through training
- Output layer: key dependent variables (AL and ACC)
- Training and testing datasets (e.g., 70%–30% split)
- Performance evaluation using Root Mean Square Error (RMSE)

The relative importance of predictors was assessed using sensitivity analysis, allowing identification of the most influential variables.

5.1 Demographic Profile of Respondents

Table 1 shows the demographics of the respondents. Subsequently, there were 502 valid responses were analysed for a further SEM–ANN analysis.

Table 1
Demographic Characteristics of Respondents (N = 502)

Variable	Category	Frequency	Percentage (%)
Gender	Male	256	51.0
	Female	238	47.4
	Prefer not to say	8	1.6
Age	Under 18	52	10.4
	18–20	214	42.6
	21–23	176	35.1
	24+	60	11.9
Academic Level	Secondary	98	19.5
	Undergraduate	298	59.4
	Graduate	106	21.1
Field of Study	Science	212	42.2
	Social Sciences	168	33.5
	Arts	86	17.1
	Other	36	7.2

Table 1 shows a relatively equal gender distribution. In total, 51.0% participants were male, while 47.4% were female participants. Most of the respondents (77.7%) in the 18–23 age group which is generally the examination population of high-stakes programs of students. In terms of academic level, most respondents were undergraduates at 59.4%, followed by graduates at 21.1% and secondary-level students at 19.5%. The distribution of the participants is appropriate for the study context, the reason being that undergraduate students are quite often exposed to computerized assessment systems. With respect to academic fields, the respondents have been cited from different disciplines. Most of them are from Science (42.2%) and social sciences (33.5%). This shows that the results are not confined to a singular discipline.

5.2 Experience with Computerized Examinations

According to Table 2, the respondents' familiarity with computerized tests was determined. According to Table 2, a majority of the respondents had a moderate to high level of experience with computerized tests (68.5%), indicating that the sample has sufficient exposure to algorithms-based tests. Most of the respondents have taken more than two computerized examinations and in addition, 79.3% of the respondents agreed to take only more than two examinations which means that they are well aware of the variations and structure of the system. When it comes to their capabilities, the majority of the participants share moderate to high digital skill levels (86.5%) that help them interact with a computer.

Moreover, 58.1% of the sample was either familiar or very familiar with item-bank-based examinations. This aspect further confirms that the sample is suitable for evaluating algorithmic assessment mechanisms.

Table 2
Experience with Computerized Examination Systems

Variable	Category	Frequency	Percentage (%)
Experience Level	None	42	8.4
	Limited	116	23.1
	Moderate	198	39.4
	Extensive	146	29.1
Number of Exams Taken	1–2	104	20.7
	3–5	176	35.1
	6–10	142	28.3
	More than 10	80	15.9
Digital Skill Level	Low	68	13.5
	Moderate	238	47.4
	High	196	39.1
Familiarity with Item Banks	Not familiar	72	14.3
	Slightly familiar	138	27.5
	Familiar	192	38.2
	Very familiar	100	19.9

5.3 Initial Perceptions of Computerized Examination Systems

As seen in Table 3, the respondents' level of awareness and knowledge towards the computerized examination system was very high, as shown by their mean scores ranging from 3.85 to 4.10. The respondents agree strongly on questions being selected automatically (M = 4.02) and that they were comfortable with computer use during high-stakes examinations (M = 4.10). Thus, demonstrating a positive orientation towards digital assessment environments. Yet, the average values of the items relating to adaptive difficulty are relatively low among the respondents (M = 3.85), which shows that not all the respondents fully understand the concept behind testing based on algorithms. As students are

familiar with the working of computerized exams but only partially aware of the system processes, this may affect their thinking on the issues of fairness, trust, and legitimacy.

Table 3
Descriptive Statistics of Experience-Based Perception Items

Code	Item	Mean	Std. Deviation
E1	Different students receive different questions	3.98	0.86
E2	Exams adjust difficulty dynamically	3.85	0.91
E3	Questions are selected automatically	4.02	0.83
E4	Comfortable using computers in exams	4.10	0.79

5.4 Measurement Model Assessment (Reliability and Validity)

To test the adequacy of the measurement model, reliability and validity were tested according to the standard criteria, which include indicator reliability, internal consistency reliability, convergent validity, and discriminant validity (Hair et al., 2021).

5.4.1 Indicator Reliability and Convergent Validity

We measured the reliability of the indicators through factor loadings and tested convergent validity using Average Variance Extracted (AVE). As indicated by the Hair et al. (2021) study, factor loading has to be equal to or greater than .70, while average variance extracted (AVE) has to be equal to or greater than .50.

Table 4
Factor Loadings and Convergent Validity

Construct	Item	Loading
Statistical Equivalence (SE)	SE1	0.812
	SE2	0.845
	SE3	0.871
	SE4	0.836
System Transparency (ST)	ST1	0.823
	ST2	0.857
	ST3	0.878
	ST4	0.841
Algorithmic Opacity (AO)	AO1	0.791
	AO2	0.834
	AO3	0.862
	AO4	0.819
Item Bank Exposure (IBE)	IBE1	0.804
	IBE2	0.839
	IBE3	0.861
	IBE4	0.822
Perceived Fairness (PF)	PF1	0.856
	PF2	0.879
	PF3	0.902
	PF4	0.868
Trust (TR)	TR1	0.874
	TR2	0.892
	TR3	0.907
	TR4	0.883
Algorithmic Legitimacy (AL)	AL1	0.861
	AL2	0.889

Construct	Item	Loading
	AL3	0.905
	AL4	0.877
Acceptance (ACC)	ACC1	0.842
	ACC2	0.871
	ACC3	0.895
	ACC4	0.864
Explanation (EXP)	EXP1	0.833
	EXP2	0.861
	EXP3	0.884
	EXP4	0.852

The factor loadings are greater than 0.70 (recommended threshold) for all items as shown in Table 4. It shows that all items represent their constructs sufficiently. Moreover, constant high loadings shown by measurement items of all constructs establish their high convergent validity.

5.4.2 Internal Consistency Reliability

Internal consistency reliability was assessed using Cronbach's alpha (α) and Composite Reliability (CR). Values above 0.70 are considered acceptable (Hair et al., 2021).

Table 5
Reliability and Convergent Validity

Construct	Cronbach's Alpha	CR	AVE
SE	0.871	0.912	0.722
ST	0.884	0.919	0.739
AO	0.856	0.903	0.701
IBE	0.868	0.908	0.711
PF	0.902	0.931	0.771
TR	0.914	0.939	0.793
AL	0.908	0.934	0.779
ACC	0.889	0.922	0.748
EXP	0.875	0.914	0.726

The values of Cronbach's alpha and composite reliability of all the constructs are higher than 0.70 (refer to Table 5), proving internal consistency. In addition, the AVE values of all constructs exceed 0.50, which indicates adequate convergent validity. The constructs are reliable and capture a substantial amount of variance in their respective indices, as evidenced by these results.

5.4.3 Discriminant Validity

The Heterotrait-Monotrait ratio (HTMT) was utilized to test discriminant validity. Values of HTMT below 0.85 suggest satisfactory discriminant validity (Henseler et al. 2015).

Table 6
HTMT Matrix

Construct	SE	ST	AO	IBE	PF	TR	AL	ACC	EXP
SE	—								
ST	0.621	—							
AO	0.584	0.645	—						
IBE	0.593	0.612	0.578	—					
PF	0.674	0.731	0.689	0.642	—				
TR	0.612	0.695	0.663	0.598	0.742	—			
AL	0.598	0.672	0.651	0.587	0.726	0.781	—		
ACC	0.563	0.641	0.622	0.574	0.701	0.759	0.794	—	
EXP	0.592	0.714	0.681	0.603	0.735	0.712	0.698	0.665	—

According to Table 6, all the HTMT values fell under the threshold of 0.85, which proved the discriminant validity. This shows that no constructs are empirically equal and that each construct captures a unique aspect of the model. Along with checking indicator reliability, internal consistency, and convergent validity, the current study further examined discriminant validity and multicollinearity to validate the measurement model. In accordance with prescribed SEM guidelines, discriminant validity was evaluated using the Fornell-Larcker criterion while collinearity among indicators was evaluated using variance inflation factor values(Fornell & Larcker, 1981; Hair Jr et al., 2021; Kock, 2015).

5.4.3 Discriminant Validity: Fornell–Larcker Criterion

According to the Fornell–Larcker criterion, the square root of AVE of each construct should be greater than the correlations it has with all other constructs. According to Fornell & Larcker (1981), it means a construct shares more variance with indicators than all the constructs in the model.

Table 6
Fornell–Larcker Criterion

Construct	ACC	AL	AO	IBE	PF	RLC	SE	ST	TR
ACC	**0.785**								
AL	0.861	**0.811**							
AO	0.514	0.546	**0.820**						
IBE	0.501	0.518	0.562	**0.780**					
PF	0.595	0.593	0.577	0.611	**0.791**				
RLC	0.661	0.646	0.676	0.568	0.658	**0.778**			
SE	0.576	0.559	0.626	0.549	0.599	0.558	**0.821**		
ST	0.395	0.428	0.487	0.440	0.412	0.432	0.551	**0.710**	
TR	0.630	0.637	0.690	0.547	0.656	0.881	0.584	0.437	**0.767**

Table 6 shows that most of the constructs satisfy the Fornell–Larcker criterion as the diagonal elements are greater than inter-construct correlations. Nevertheless, it is worth noting two exceptions. First, the relationship between algorithmic legitimacy (AL) and acceptance (ACC) (r = 0.861) is greater than the square root of AVE for both constructs, AL (0.811) and ACC (0.785). The association between result logic clarity/explanation (RLC) and trust (TR) (r = 0.881) is twice the square root of AVE for both constructs, RLC = 0.778 and TR = 0.767. These findings indicate the likelihood of a discriminant validity issue between these construct pairs. In essence, this pattern is not surprising. In high-stakes algorithmic assessment, students may think that legitimacy and acceptance are very similar evaluations. Likewise, explanation clarity and trust may be conceptually similar to understandable decision logic, which is often a more direct basis for confidence in the system. However, from a measurement standpoint, these high intercorrelations indicate that the constructs are very close empirically and thus should be interpreted with caution. More and more SEM literature recommends triangulating Fornell–Larcker with other diagnostics, particularly HTMT, since Fornell–Larcker may fail at picking up all discriminant validity issues (Hair Jr et al., 2021; Henseler et al., 2015; Soormo et al., 2024). It is therefore essential that these findings be openly reported as a localized discriminant validity issue, rather than left unreported.

5.4.4 Multicollinearity Assessment

Variance inflation factors (VIF) values were used to assess multicollinearity. As per Hair et al. (2021), whenever VIF values are less than 3.3, it does not indicate a collinearity problem. Kock (2015) recommended using a conservative cut-off of 3.3 for PLS-SEM.

Table 7
Indicator VIF Values

Item	VIF	Item	VIF	Item	VIF
ACC01	1.440	AL01	1.817	AO01	1.901
ACC02	1.670	AL02	1.871	AO02	2.014
ACC03	1.823	AL03	1.829	AO03	1.975
ACC04	1.489	AL04	1.556	AO04	1.624
IBE01	1.402	PF01	1.230	RLC01	1.474
IBE02	1.611	PF02	1.965	RLC02	1.594
IBE03	1.648	PF03	2.466	RLC03	1.654
IBE04	1.602	PF04	1.785	RLC04	1.474
SE01	1.778	ST01	1.094	TR01	1.466
SE02	1.903	ST02	1.894	TR02	1.541
SE03	1.974	ST03	1.961	TR03	1.538
SE04	1.696	ST04	1.994	TR04	1.526
RLC × PF	1.000				

According to Table 7, the VIF values all fall within 1.000 to 2.466. No value approaches the conservative value of 3.3, and none gets close to the liberal value of 5.0. The VIF of the PF03 is 2.466, but it is acceptable, according to the results. This means that multicollinearity are not severely affected in the measurement model. In a similar fashion, the interaction term RLC × PF displays a VIF of 1.000, indicating that there is no collinearity. These collinearity diagnostics imply that the indicators measure sufficiently distinct shared variances and parameter estimates are unlikely to be negatively impacted by their collinearity. This means that the specific constructs examined may have some overlap, but that overlap is not severe enough to threaten model estimation.

The measurement model shows an adequate psychometric quality. The constructs satisfy the requirements of internal consistency reliability, convergent validity, and acceptable collinearity. In general, discriminant validity is supported, except that the Fornell–Larcker criterion shows AL–ACC and RLC–TR are conceptually very close. Instead of disconfirming the model, these findings imply that the affected constructs are highly interrelated in the perceptions of respondents. Therefore, they should be interpreted as theoretically adjacent but empirically distinct with caution. According to earlier studies, the explanatory features considered to be fairness-related show strong ties to trust, and legitimacy judgments probably closely correspond to acceptance outcomes in AI-supported decision-making settings (Schilke & Reimann, 2026).

5.5 Structural Model Assessment

To test the proposed hypotheses, the structural model was assessed through path coefficients, significance levels and R^2, f^2 and Q^2 as indicators of explanatory power. Bootstrapping with 5,000 resamples was performed to assess the significance of the relationships (Hair et al., 2021).

5.5.1 Coefficient of Determination (R^2)

Table 8
R^2 Values

Construct	R^2	Adjusted R^2
Acceptance (ACC)	0.752	0.751
Algorithmic Legitimacy (AL)	0.460	0.458
Perceived Fairness (PF)	0.497	0.493
Trust (TR)	0.787	0.786

As illustrated in Table 8, the model shows great explanatory power. The R^2 value for acceptance (ACC = 0.752), which indicates that about 75.2% of the variance in acceptance is explained by the model, is considered substantial (Hair et al., 2021). Likewise, variance in trust (TR = 0.787), meaning the predictors strongly explain students' confidence in assessments. The R^2 values of perceived fairness (PF = 0.497) and algorithmic legitimacy (AL = 0.460) indicate moderate explanatory power and moderate commentary engine variance respectively. In conclusion, we may confirm that the model offers a good capacity to explain the key dependent constructs in this study.

5.5.2 Hypothesis Testing (Direct Effects)

Table 9. Hypothesis Testing Results (Direct Effects)

H#	Path	β	t-value	p-value	Result
H1	SE → PF	0.279	5.272	0.000	Supported
H2	ST → PF	0.008	0.179	0.858	Not Supported
H3	AO → PF	0.209	4.412	0.000	Supported
H4	IBE → PF	0.337	6.921	0.000	Supported
H5	PF → TR	0.132	3.964	0.000	Supported
H6	PF → AL	0.307	5.373	0.000	Supported
H7	TR → AL	0.436	7.795	0.000	Supported
H8	AL → ACC	0.774	23.754	0.000	Supported
H9	TR → ACC	0.136	3.784	0.000	Supported
H10	RLC × PF → TR	-0.025	1.122	0.262	Not Supported

According to Table 9 and Fig. 4, most of the assumed relationships are statistically significant. Statistical equivalence (β = 0.279, p < 0.001), algorithmic opacity (β = 0.209, p < 0.001), and item bank exposure (β = 0.337, p < 0.001) have a strong and significant effect on perceived fairness, thus supporting H1, H3, and H4. Out of these, item bank exposure has the strongest effect, which means that being familiar with computerized systems affects people's fairness perceptions.

Believably, the perceived fairness of the system is not impacted by system transparency (β = 0.008, p = 0.858), thus the H2 is rejected. It appears that mere transparency is insufficient to convince customers about the fairness of a situation or offering. As is evident from the results, perceived fairness has a significant influence on both trust (β = 0.132, p < 0.001) and algorithmic legitimacy (β = 0.307, p < 0.001). Therefore, hypotheses 5 and 6 are supported. Moreover, trust was found to be a significant predictor of legitimacy (β = 0.436, p < 0.001), thus providing confirmation of H7. An analysis of the results suggests that at the outcome level, algorithmic legitimacy has a very strong impact on acceptance (β = 0.774, p < 0.001). Thus, legitimacy drives acceptance of the system. Trust has a substantial but less powerful direct effect on acceptance (β = 0.136, p < 0.001), thus supporting H9. In conclusion, the moderating effect of explanation (RLC × PF → TR) is insignificant (β = -0.025, p = 0.262), with explanation not strengthening the association between perceived fairness and trust. Thus, H10 is unsupported.

5.5.3 Indirect Effects (Mediation Analysis)

Table 10
Indirect Effects

Path	t-value	p-value	Result
AO → PF → AL	4.123	0.000	Significant
AO → PF → TR	2.702	0.007	Significant
IBE → PF → AL	4.950	0.000	Significant
IBE → PF → TR	3.714	0.000	Significant
PF → TR → ACC	7.053	0.000	Significant
RLC → TR → ACC	8.771	0.000	Significant
SE → PF → AL	3.911	0.000	Significant
ST → PF → AL	0.177	0.860	Not Significant

According to the mediation analysis (as finding as highlighted in Table 10), perceived fairness mediates the impact of system-level driving forces on trust and legitimacy. In particular, algorithmic opacity, exposure of item bank, and statistical equivalence affect legitimacy and trust indirectly through perception of fairness. Moreover, trust serves as a mediator between fairness and acceptance, further establishing its significance as a psychological mechanism. Nonetheless, transparent systems have no significant indirect effects, thus verifying their limited presence in this framework.

5.5.4 Effect Size (f^2) and Predictive Relevance (Q^2)

The effect size (f^2) of each of the predictors on the endogenous constructs was determined. As per (Cohen, 1998), small, medium, and large effects are represented by 0.02, 0.15, and 0.35, respectively. The findings reveal that.

- The large size effect of AL → ACC indicates the dominant influence of friendly attitudes on acceptance.
- The TR to AL correlation is large, indicating trust is an important concern.
- IBE → PF displays a medium effect, which suggest experience effects.
- Other relationships are generally small to moderate effect sizes.

Predictive relevance (Q^2) values, which were obtained through blindfolding procedures, were all positive, indicating strong predictive capability of the model (Hair et al., 2021). The explanatory and predictive power of the structural model is pronounced. The majority of hypothesized relationships are supported and the framework is robust. Researchers find that perceived fairness and trust play central roles in algorithmic legitimacy and acceptance. The findings also show significant results like transparency not being significant. Meaning transparency alone may not affect views of fairness unless there is a meaningful explanation and understanding. Also, the failure of presence of the moderation effect implies that, in this case, the explanation might work as a direct predictor instead of conditional.

5.6 Artificial Neural Network (ANN) Analysis

To complement the SEM results and capture potential non-linear relationships, this study employed Artificial Neural Network (ANN) analysis. ANN is a powerful machine learning technique capable of modeling complex, non-linear interactions among variables, thereby enhancing predictive accuracy beyond traditional SEM approaches (Al-Emran et al., 2024). Following prior studies, a multilayer perception (MLP) architecture was used with one hidden layer. The dataset (N = 502) was randomly divided into training (90%) and testing (10%) subsets across ten neural networks to ensure robustness and avoid overfitting(Al-Emran et al., 2024; Santin et al., 2016). The ANN analysis was conducted separately for two key dependent variables:

- Algorithmic Legitimacy (AL)
- Acceptance (ACC)

5.6.1 ANN Results for Algorithmic Legitimacy (AL)

To augment the SEM findings and capture non-linear relationship(s), we conducted an ANN analysis taking algorithmic legitimacy (AL) as the dependent variable. Using a multilayer perceptron to structure ten neural network models was done following the specified procedure and the averaged result was given a preference.

Table 11
Sensitivity Analysis for Algorithmic Legitimacy (AL)

Neural Network	AO	IBE	PF	RLC	SE	TR
NN (i)	0.70	0.69	0.95	1.00	0.38	0.75
NN (ii)	0.60	0.82	0.88	0.74	0.86	1.00
NN (iii)	0.66	0.09	0.96	1.00	0.58	0.82
NN (iv)	0.57	0.19	0.59	1.00	0.66	0.49
NN (v)	0.66	0.03	1.00	0.81	0.82	0.86
NN (vi)	0.78	0.53	0.78	1.00	0.63	0.85
NN (vii)	0.95	0.53	0.76	1.00	0.81	0.54
NN (viii)	0.81	0.24	0.84	1.00	0.82	0.67
NN (ix)	0.70	0.11	0.65	1.00	0.46	0.78
NN (x)	0.43	0.24	0.72	1.00	0.40	0.41
Average importance	**0.68**	**0.87**	**0.81**	**0.78**	**0.83**	**0.72**
Normalized importance (%)	**71.64%**	**36.14%**	**85.18%**	**100.00%**	**67.07%**	**74.95%**

According to Table 11, the result logic clarity (RLC) of the system is established as the most significant predictor of algorithmic legitimacy with a normalized importance of 100%. This finding confirms that the clear explanation of the system processes is important for the perception of legitimacy. This finding is consistent with previous scholarship indicating that explainability aids users in assessing algorithmic decisions and bolsters perceived legitimacy (Grimmelikhuijsen, 2023; Kizilcec, 2016). With a percentage of 85.18, perceived fairness comes in as the second most influential predictor. This finding of this study supports the SEM results depicting the legitimacy was significantly influenced by the fairness Thus, trust (74.95%) is rated high in predictive importance; trust as a psychological mechanism is important for fairness-legitimacy link. Notably, algorithmic opacity (71.64%) and statistical equivalence (67.07%) are also fairly important, suggesting that both system characteristics and technical fairness matter for legitimacy. In comparison, item bank exposure (36.14%) has a lower worth, indicating that previous exposure to those similarly uncertain conditions is less influential in forecasting legitimacy.

Table 12
RMSE Values for Algorithmic Legitimacy (AL)

Training N	Training SSE	Training RMSE	Testing N	Testing SSE	Testing RMSE	Total Sample
448	144.01	1.7637	54	15.175	0.530	502
442	138.00	1.7897	60	28.193	0.685	502
450	138.58	1.8020	52	16.605	0.565	502
444	132.07	1.8335	58	12.052	0.455	502
460	147.58	1.7654	42	11.599	0.525	502
452	138.14	1.8088	50	13.315	0.516	502
444	129.42	1.8521	58	14.255	0.495	502
458	134.93	1.8424	44	19.721	0.669	502
443	136.86	1.7991	59	20.136	0.584	502
453	140.95	1.7927	49	13.818	0.531	502
Mean	**138.05**	**1.805**		**16.487**	**0.556**	
SD	**5.0635**	**0.029**		**4.778**	**0.069**	

Note: SSE = Sum of Squared Errors; RMSE = Root Mean Square Error.

Table 12 shows that the ANN model for algorithmic legitimacy performs well in predicting. The RMSE value for mean testing is 0.556 whilst the RMSE value for training is 1.805. Since the first number is lower than the second number, overfitting is not occurring in this model. This model is performing well. The model's major behavior indicates that the model behaves consistently after repeat fittings. Findings indicate the ANN model can effectively capture complex relationships influencing legitimacy perceptions. Insights from SEM and ANN are complementary SEM and ANN are increasingly used to demonstrate meaningful communication for marketing and SEM in predicting pest control activity. While HMC and SEM identifies the statistically significant relationship and causal pathways, ANN reveals the relative importance and non-linear influence of the predictors (Hew et al., 2019; Sharma et al., 2021). Across both dependent variables, the ANN results highlight that

- Explanation (RLC) is the most influential predictor, even though its moderating effect was not significant in SEM
- Perceived fairness remains a central driver, confirming its mediating role
- Trust and statistical equivalence are important but secondary predictors
- Transparency plays a minimal role, consistent with SEM findings

5.6.2 ANN Results for Acceptance (ACC)

To further validate the structural model and determine potential non-linear relationships, ANN analyses were conducted with acceptance (ACC) as the dependent variable. The training and testing were done on a total of ten neural networks, where the results were averaged for getting robustness and stability (Al-Emran et al., 2024; Soomro et al., 2025).

Table 13
Sensitivity Analysis for Acceptance (ACC)

Neural Network	AO	IBE	PF	RLC	SE	TR
NN (i)	0.19	0.05	0.70	1.00	0.57	0.18
NN (ii)	0.05	0.16	0.64	1.00	0.63	0.20
NN (iii)	0.19	0.08	0.62	1.00	0.63	0.12
NN (iv)	0.19	0.14	0.55	1.00	0.50	0.47
NN (v)	0.05	0.11	1.00	0.92	0.73	0.24
NN (vi)	0.42	0.54	1.00	0.98	0.47	0.81
NN (vii)	0.24	0.39	0.96	1.00	0.81	0.53
NN (viii)	0.03	0.07	0.95	0.90	1.00	0.63
NN (ix)	0.32	0.25	0.75	1.00	0.48	0.34
NN (x)	0.43	0.24	0.72	1.00	0.40	0.41
Average importance	**0.42**	**0.37**	**0.49**	**0.49**	**0.64**	**0.67**
Normalized importance (%)	**21.50%**	**20.48%**	**80.59%**	**100.00%**	**63.45%**	**40.21%**

Based on the information provided in Table 13, result logic clarity (RLC) is the most influential predictor of acceptance, with a normalized importance of 100%. This indicates its major influence on the willingness to accept algorithm-driven examination systems. The findings suggest that an open exchange of scoring and decision logic is vital for user acceptance. This further confirms previous findings emphasizing the importance of explainability for AI systems (Kostopoulos et al., 2024; Donghee Shin, 2021). The second most important element is perceived fairness (80.59%) and it strengthens the SEM results as a key predictor. A report analyzes the impact of statistical equivalence in acceptance generation. Specifically, the impact of users' perception of fairness additionally low technical variance. Overall findings are indicating that algorithmic opacity (21.50%) and item bank exposure (20.48%) are less important. Thus, these elements influence acceptance in an indirect manner. In addition, they do not serve as direct indicators. The value of trust, at a rate of 40.21 percent, bears a moderate significance meaning in the sense that it is important for acceptance but less than fairness and explanation according to non-linear modeling.

Table 14
RMSE Values for Acceptance (ACC)

Training N	Training SSE	Training RMSE	Testing N	Testing SSE	Testing RMSE	Total Sample
448	128.85	1.864	54	13.33	0.49	502
450	128.87	1.868	52	16.41	0.56	502
447	127.86	1.869	55	6.095	0.33	502
440	120.28	1.912	62	12.80	0.45	502
456	129.53	1.876	46	17.15	0.61	502
453	109.69	2.032	49	18.65	0.61	502
447	113.68	1.982	55	16.77	0.55	502
454	137.48	1.817	48	8.677	0.42	502
444	117.19	1.946	58	13.93	0.49	502
450	109.27	2.029	52	7.69	0.38	502
Mean	**122.27**	**1.919**		**13.15**	**0.49**	
SD	**9.125**	**0.070**		**4.12**	**0.09**	

Note: SSE = Sum of Squared Errors; RMSE = Root Mean Square Error.

The ANN model exhibits strong predictive performance as shown in Table 14. The mean testing RMSE value (0.49) is significantly lower than the training RMSE (1.919). This indicates the model possesses good generalization ability and isn't overfitting. The small standard deviation gives additional confirmation that this model is stable across multiple runs. The ANN model is efficient in capturing non-linear performance relationships and giving accurate prediction of the acceptance of marriages. The low error rates and stability of the ANN method further attest to its robust applicability to SEM analysis. The findings indicate that explanation is primarily a direct predictor rather than a moderator, which provides further insight into the functional role of explanation in algorithms. The findings from ANN validate and enhance the SEM results by establishing that explainability and perceived fairness are the two major determinants of algorithmic legitimacy and acceptance. The pre-eminence of explanations reveals the user-centred design in system design. Revealing the logic behind a user's decision enhances understanding and trust. Moreover, results from ANN indicate some non-linear relationship presence between variables, not captured entirely by SEM.

6. Discussion

This research was driven by a main issue in current computerized high-stakes evaluation: technical fairness does not guarantee perceived fairness, trust, legitimacy or acceptance. Different test forms designed to psychometrically equate the examination are sufficient to ensure that each student is

assessed on the same scale. However, learners question fairness when the test form differ, item selection is automatic, or scoring logic is opaque. The results give important evidence that students' acceptance of algorithm-driven examinations depends less on whether they are technically sound and more on the perception, understanding, and legitimation of these processes.

6.1 System-level predictors of perceived fairness

The finding indicates that participants whose rewards were statistically equivalent judged the distribution as more fair. This study shows that students are more likely to endorse computerized examinations as fair when they believe that test forms are comparable in terms of difficulty and scoring criteria. As such, one could say that the technical fairness still remains a necessary condition for legitimacy in algorithmic assessment systems. The result further indicates the recognition of statistical equivalence as a fairness mechanism by students in order for it to matter. This is consistent with the fairness literature, which finds that people assess algorithmic systems based on not only outcomes, but also whether procedures appear consistent and justified (Wang et al., 2020; Newman et al., 2020). A perceived level of fairness was strongest associated with item bank exposure (H4: $\beta = 0.337$, $p < .001$). Students who are used to item-bank-based testing realize that getting different questions does not imply that they are being unfairly tested. It is important because it shows that prior experience lowers uncertainty and support's fair interpretation of assessment processes. This also lends further support to studies arguing that user literacy as well as familiarity affect individuals' responses to algorithmic systems. The perceived fairness of system transparency was unexpectedly found not to be significant (H2: $\beta = 0.008$, $p = .858$). This result is significant and has theoretical meaning. Transparency may not boost perceptions of fairness if information is too generic, technical or inapplicable to students personally. As per (Kizilcec, 2016; Ngo, 2025), this supports the argument of the " transparency paradox" which argues that more information does not lead to more trust/fairness in case users cannot understand it. So, simply saying that the system is transparent is probably not enough to students; it should be translated into elucidation in high-stakes exams. The path of algorithmic opacity and perceived fairness (H3: $\beta = 0.209$, $p < .001$) was not a surprise. Broadly speaking, opacity tends to 'reveal' fairness perceptions. Nonetheless, the positive coefficient suggests that students who are more aware of the complexity of the system also recognize the necessity of algorithmic procedures to maintain standardization and equivalence. It might be that respondents do not view opacity as negative per se. Rather, they may see the system as technologically sophisticated or an expression of institutional power. Similar mixed findings have been reported ADM studies, where users accept opaque systems sometimes because of their belief in the system as reliable, standardized, or authorized by the institution itself (Grimmelikhuijsen, 2023; Donghee Shin, 2020). This outcome ought to be contextualised rather than deemed contradictory.

6.2 Perceived fairness, trust, and algorithmic legitimacy

The analysis shows that perceived fairness positively influences trust (H5: $\beta = .132$, $p < .001$). Despite its small effect size, the association is statistically significant and theoretically interesting. The students'

perceptions can influence whether they try to explore ways to get around the system. The theory of procedural justice proposes that when procedures are perceived to be fair, it boosts officers' and the public's confidence in authorities, institutions, and systems (Brockner et al., 2000; Colquitt & Rodell, 2011). Fairness serves as a signal to the user in algorithmic context that the system is not biased. The findings also accentuate the positive effect of perceived fairness on algorithmic legitimacy (H6: $\beta = 0.307$, $p < .001$). At the core of the study, this finding lies. According to research, fairness not only generates trust but also maintains that a computer assessment system is credible enough to be used in official exams. As per legitimacy theory, systems seen as appropriate, justified, and consistent with relevant social norms get accepted (Suchman, 1995). Grimmelikhuijsen and Meijer (2022) Furthermore, as H7 attests, there is a significant correlation between user trust in the algorithmic fairness and legitimacy of the different pieces of Information and communication technology. In this case, users who trust the algorithm that it is reliable and accurate chances of belonging to a certain group will also have high legitimacy attribution to the algorithm. Pupils would tend to accept the exams as legitimate, when they perceive the system as dependable, accurate and fair. The outcomes are consistent with existing studies, indicating that legitimacy in any setting supported by AI-dependent decisions is a high function of trust(Choung et al., 2025; Schilke & Reimann, 2026).

6.3 Legitimacy and acceptance of computerized assessment

The modeling results indicate the strongest direct effect in the model was algorithmic legitimacy on acceptance (H8: $\beta = 0.774$, $p < .001$). One of the key findings of this study is this. It shows the students' acceptance of computerized high-stakes examinations shall largely depend on the perception of the legitimacy of the system. Consequently, legitimacy is not an ancillary outcome; it is a key driver of acceptance. An effective yet illegitimate system may be rejected by students on the grounds of its illegitimacy or lack of appropriateness. Trust also has a significant direct impact on acceptance (H9: $\beta = 0.136$, $p < .001$), although the impact is less than legitimacy. Trust might lead to acceptance, but its effect may operate largely through legitimacy. In practical terms, students may trust certain aspects of the system, but full acceptance requires a broader belief that the system is institutionally valid and suitable for high-stakes use.

The findings from the mediation study indicate that perceived fairness and trust are important psychological mechanisms that connect system-level features to legitimacy and acceptance. The experience of trust, legitimacy and acceptance is influenced indirectly by statistical equivalence, item bank exposure, and algorithmic opacity through perceived fairness. This confirms that students do not respond directly to technical features. Rather, they use fairness judgments to make sense of features. It is also noteworthy that the clarity/explanation of result logic has a non-significant moderation effect on the PF → TR relationship (H10: $\beta = -0.025$, $p = .262$). In this model, being explained does not fortify the link between fairness and trust. The results reflect that, instead, explanation may function more strongly as a direct predictive factor than as a moderator. This corroborates findings that explanations can

enhance comprehension or acceptance but dependent on the content, timing, or how users interpreted the content(Kizilcec, 2016; Sullivan & Weger, 2025).

The finding of ANN complements the SEM results shows the strongest predictor of legitimacy and acceptance under non-linear condition. The clarity of the logic of the result was the most significant predictor of algorithmic legitimacy. Perceived fairness and trust were other significant predictors. Thus, though SEM revealed the direct theoretical pathways, ANN indicated that clarity of explanation has strong predictive power in shaping legitimacy perceptions. ANN once again identified result logic clarity as the most influential predictor of acceptance followed by perceived fairness and statistical equivalence. This shows how acceptance by students largely depends on whether they understand how the system works and how the results are obtained. The findings confirm the capability of the hybrid SEM–ANN analysis as while SEM explores theory-based relationships, ANN helps to identify predictive importance and non-linear patterns (Al-Emran et al., 2024; Santin et al., 2016). An important conclusion from the analytical findings of the ANN is that being able to explain something has a direct design as opposed to a moderator as a statistical value. The SEM did not support moderation hypothesis but result logic clarity ranked highest in ANN so this is explained. As a practical matter, students may not use explanations to alter a fairness–trust relationship; rather, they may evaluate clarity of explanations as an independent signal of system quality. The study suggests that algorithmic legitimacy is achieved through a step wise process where system characteristics leads to perception of fairness leads to trust, leads to legitimacy, which leads to acceptance. The practical message that can be inferred is that technical validity must have perceptual and communicative legitimacy. While we must ensure psychometric equivalence, students also must believe and understand it is fair. This study thus connects psychometric fairness to algorithmic legitimacy in the ADM literature. The study extends on earlier work related to fairness, transparency and trust. It shows that in high stakes assessment systems, acceptance is not driven by transparency alone, but instead by perceptions of fairness, trust, legitimacy and clarity of explanation. This lends weight to the stronger claims that algorithmic systems should be designed to be fair, but should also appear to be fair, explainable, and institutionally legitimate.

7.1 Theoretical Implications

This research makes important theoretical contributions to algorithmic decision-making, educational assessment and technology acceptance literature. This study builds on the existing literature by incorporating psychometric fairness. As past work tended to examine fairness as either a technical construct (e.g., statistical validity) or a perceptual construct (e.g., perceived fairness), the current work helps bridge the two by showing how statistical equivalence results in perceived fairness. This integration enriches fairness theory by showing how technical correctness alone is not enough unless it is recognised cognitively and socially by end-users. Moreover, the paper adds to algorithmic legitimacy theory by validating a multi-stage legitimacy formation process empirically. Specifically, the findings show that legitimacy cannot be derived from the features of the system. It is produced in a sequential manner through perceived fairness and trust. This extends legitimacy theory by showing how legitimacy varies through psychological mediation in algorithmic contexts rather than institutions or authorities

(Suchman, 1995). In addition, the results offer important insights into the role of comprehension and transparency in algorithmic systems. In literature, most documents assumed that system transparency and the assessment of fairness are connected. It counters the notion that transparency is a panacea for all problems of trust and fairness in AI systems. The results show that explanation (result logic clarity) matters more directly and critically, particularly as revealed by ANN analysis. This shows that interpretability, not transparency, is what drives user acceptance which adds to the ongoing debate on the “transparency paradox”. Moreover, the study makes an important methodological contribution by showing the utility of a hybrid SEM-ANN in algorithm studies. While the SEM analysis confirms the relationships supported by the theory, the results of the ANN analysis reveal non-linear patterns, the importance of the predictors and their interactions which provide deeper insights into how the user behaves. This dual approach not only boosts the explanatory component of research, but it also helps to enhance the predictive part in behavioral sciences and AI. The study extends the technology acceptance literature by proposing algorithmic legitimacy as an important antecedent to acceptance. Although, TAM, which is a traditional model, tell us to look at the perceived usefulness as well as ease of use, but this study tells us that in the high stakes contexts, perceptions of legitimation and fairness are more important than usability alone. It indicates that we must scrutinize the acceptance of AI systems, especially in sensitive domains such as education from a wider socio-technical lens.

7.2 Practical Implications

The findings of the study can benefit policymakers, educational institutions, developers of tests, and designers of algorithm-based systems. The findings emphasize the importance of communicating statistical equivalence effectively. Students are largely unaware of the psychometric procedures that were used to equate different forms. As a result, institutions should develop clear explanations of the exam forms and their equating to implement and perceive fairness. Visual explanations, pre-exam briefings, or post-test feedback reports can make it happen. Additionally, the experiences and familiarity of users shape perceptions of fairness in this study. Use of analogue question banks and exposure to mock tests and training should be given by educational institutes to allow students to get a feel of computerized testing systems since item banks practice environments have a big impact. The more we learn, the less uncertainty we have. This enables students to see variations in forms as fair rather than random. The most important factor affecting both legitimacy and acceptance is the explanation given in terms of clarity of result logic. This indicates that system designers should focus on the Explainable AI (XAI) feature of.

- Clear scoring breakdowns
- Transparent item selection logic
- Personalized feedback explanations

Incorporating these elements can greatly improve users’ comprehension and acceptance, even when systems are complex. Fourthly, the non-significant effect of transparency suggests that it is not enough to provide information. Institutions must ensure that information is usable and useful by the user. The

perception of algorithmic evidence may be improved through technical descriptions, but only if they are translated into meaning. The strong impact of algorithm legitimacy on acceptance suggests that institutions need to focus on building algorithm legitimacy through fairness, trust and communication strategies. This comprises:

- Establishing clear policies on algorithmic decision-making
- Ensuring accountability and auditability of systems
- Providing mechanisms for appeals or review of results

Such practices can enhance institutional credibility and reduce resistance to computerized assessments.

Sixth, the findings highlight the need to manage perceptions of algorithmic opacity. While some level of complexity is unavoidable, institutions should minimize unnecessary opacity by:

- Providing user-friendly interfaces
- Offering interactive explanations
- Ensuring consistency in system behavior

Reducing perceived opacity may circumvent distrust and improve fairness perceptions.

To conclude, the acceptance of algorithmic systems in important contexts is a socio-technical issue. Solely possessing technical precision is not enough. The systems should also be viewed as fair, trustworthy and legitimate. The successful implementation thus involves technical design as well as user education and transparency.

8. Conclusion

The research investigated students' perception on fairness, trust, legitimacy and acceptance in an algorithmbased high-stake exam. This study offers a better understanding of how technical and perceptual factors jointly affect user perceptions, blending psychometric principles with algorithmic decision making theory. Overall, the proposed investigations reveal that perceived fairness and trust matter as the key mechanisms of the system characteristics on algorithmic legitimacy and acceptance. Exposure to an item-bank-based system usually greatly improves perceptions of fairness, to put it simply. Furthermore, fairness correlates positively with trust and legitimacy. Out of every relationship, algorithmic legitimacy is the strongest predictor of acceptance among a host of relationships which indicates that this particular relationship is the determinant if students accept the computerized assessment. The study shows that while transparency may not affect fairness perceptions, the clarity of result logic, explanation, plays an important role, especially in predictive (ANN) analysis. This makes it clear that students prefer to be informed about how decisions are made, which matters the most to them. As the results indicate, algorithmic systems must be technically sound and perceptually acceptable to gain user trust and institutional legitimacy. By establishing connections between objective

fairness (statistical validity) and subjective fairness (user perception) of a high-stakes assessment system, the analyses in this paper contribute to the literature. It highlights that algorithmic systems should be accurate, but should also be understandable, trustworthy, and socially legitimate. The given information offers useful hint to educational institutions and policy makers in implementing fair and acceptable computerized examination systems in the system of education .

9. Limitations and Future Research Directions

The study sheds light on several aspects of the research regarding algorithmic legitimacy in high-stakes computerised examinations. There are restrictions that the paper has. The primary drawback of this study is a cross-sectional research design which limits the realization of causal inference over time. Although the SEM had a significant theoretical inference, perceptions of fairness, trust, and acceptance may change after repeated exposure. Longitudinal designs could be a focus of future studies that assess whether perceptions change with continued use of computerised examinations. Also, we cannot rule out the congruency effect and the common method bias since we employed self-report measures. Statistical techniques can help eliminate those options but future studies could use more than one source of data or measure behaviour or experiment. In addition, the study confines itself to a specific school context, limiting its generalizability to other institutional sites or contexts. Our beliefs about fairness and trust in algorithms are likely shaped by culture, institutions and the technological state of affairs. Future research should involve cross-country comparisons or multiple institutions in order to improve external validity. While the study employs SEM–ANN hybrid analysis, analysis is pre-specified theory of the study. Even though ANN captures the non-linear relationship, it does not go deeper into other learning architectures or other machine learning algorithms. Subsequent research may advance this work by utilizing more advanced AI approaches and employing recent developments such as deep learning models and explainable AI frameworks. According to the study, the moderating factor is explanation, but the findings show that explanation might work better as an explanatory factor. In future studies, researchers should expand this conception by examining different kinds of explanations (e.g. procedural, outcome, personalized) in terms of their differential effects on fairness and trust. Inclusion of the sixth variable concerned statistical equivalence, transparency and opacity. Nevertheless, due to space constraints, many others cannot be added. The study avoided perceived usefulness, emotions, algorithmic literacy and institution trust. Future research might extend this model to capture a broader range of factors that influence the acceptance of algorithmic systems. The research only examines the viewpoint of the students. Teachers, school managers or policymakers are other stakeholders but may have a different opinion of fairness and legitimacy. The future works must involve stakeholders that improve the understanding of algorithmic assessment systems. No matter its shortcomings, the study provides a useful starting point for future research as it highlights important insights over the relationships between technical design, user assessment and institutional legitimacy.

Declarations

Ethical approval

This study was reviewed and approved by the Institutional Review Board (IRB) at Yarmouk University, Jordan (IRB/2025/418), and all procedures were performed in accordance with the ethical standards of the institutional research committee and with the 1964 Helsinki Declaration and its later amendments.

Consent to participate

Informed consent was obtained from all individual participants included in the study. For school students under the legal age, informed consent was obtained from their parents or legal guardians.

Consent to publish

Not applicable.

Authors' Contribution Declaration

First author: Wrote the main text of the manuscript and conducted the data analysis.

Second author: Supervised the study, provided valuable feedback, and reviewed and revised the manuscript. Both authors reviewed the final manuscript.

Ethics& Consent

Approval was obtained from the Research Ethics Committee (IRB) of Yarmouk University.

Data Availability

The data supporting these findings is available from the author.

Competing Interest

The authors declare that there is no conflict of interest.

Funding declaration

This research did not receive any external funding.

Clinical trial number: Not applicable.

Ethical Approval and Informed Consent:

This study was reviewed and approved by the Institutional Review Board (IRB) at Yarmouk University, Jordan (IRB/2025/418). Informed consent was obtained from all study participants.

Publication approval:

All participants have given their consent for publication.

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Figures

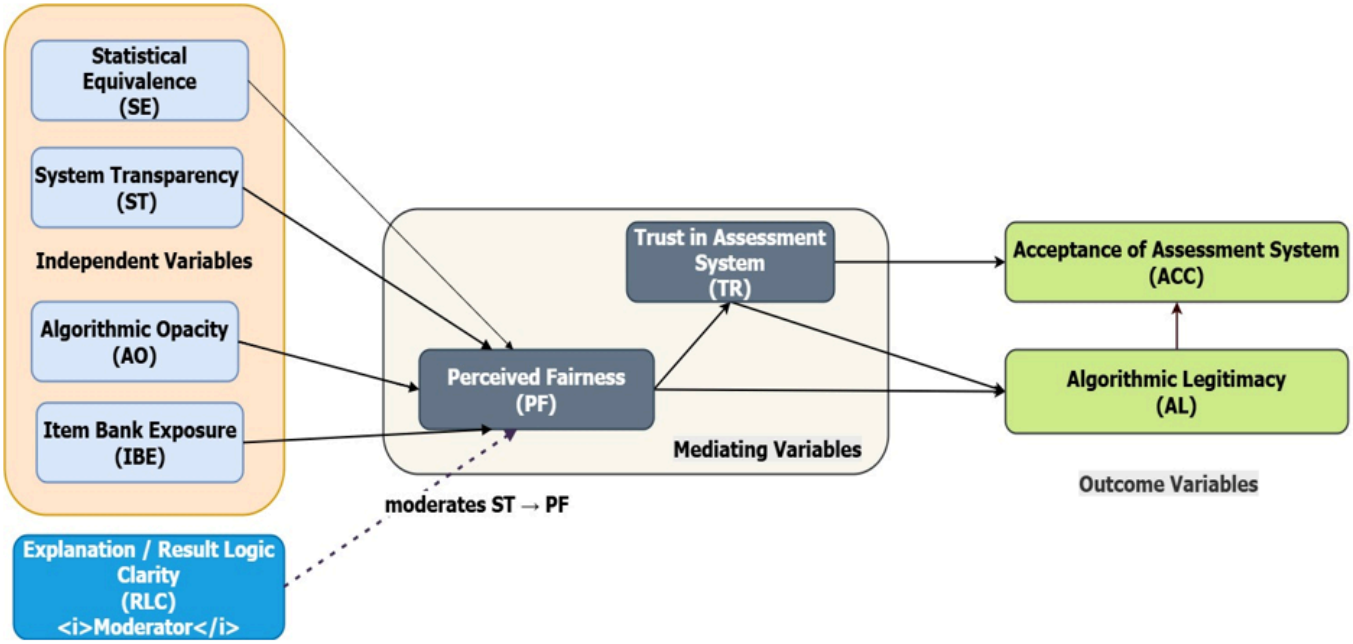


Figure 1

Proposed Conceptual Research of the Study

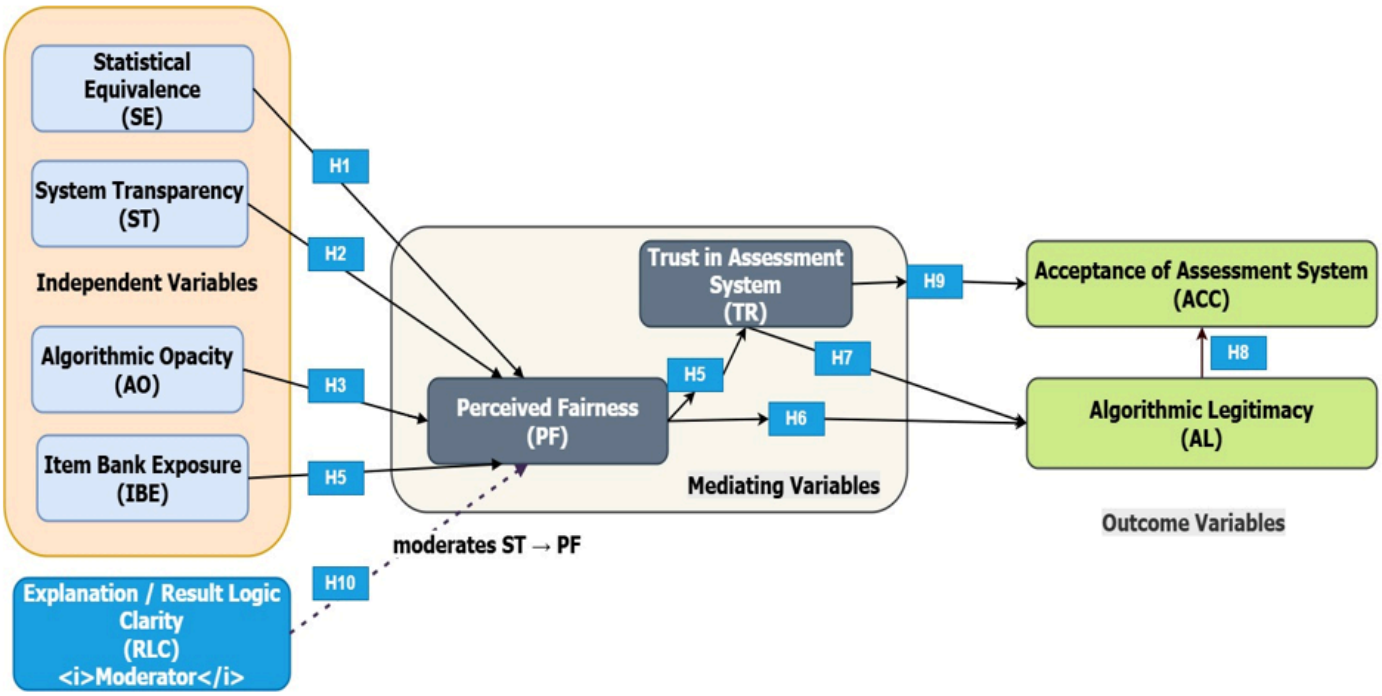


Figure 2

Proposed Research Model Relationships (Hypothesis)

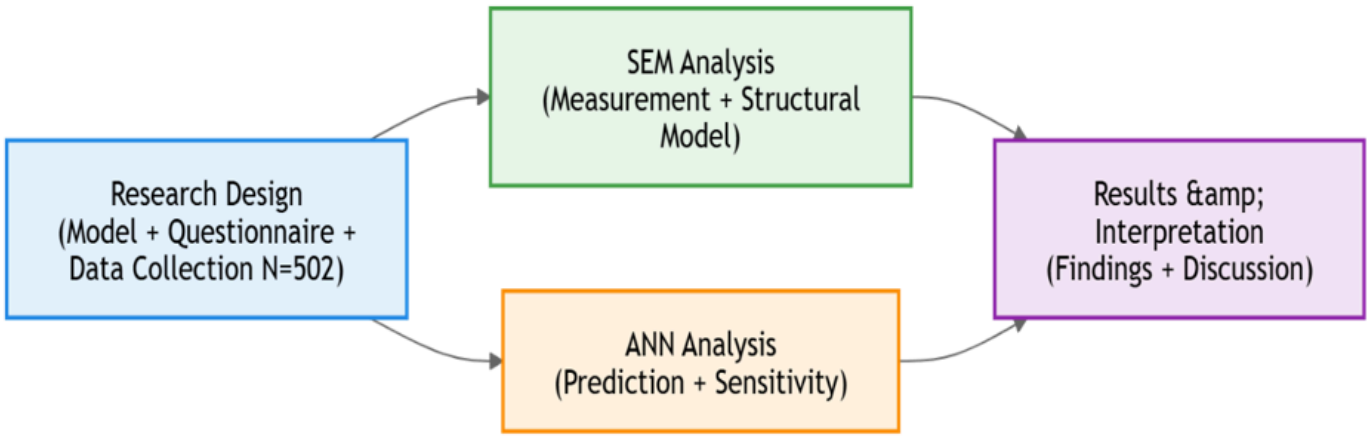


Figure 3

Research Design Process

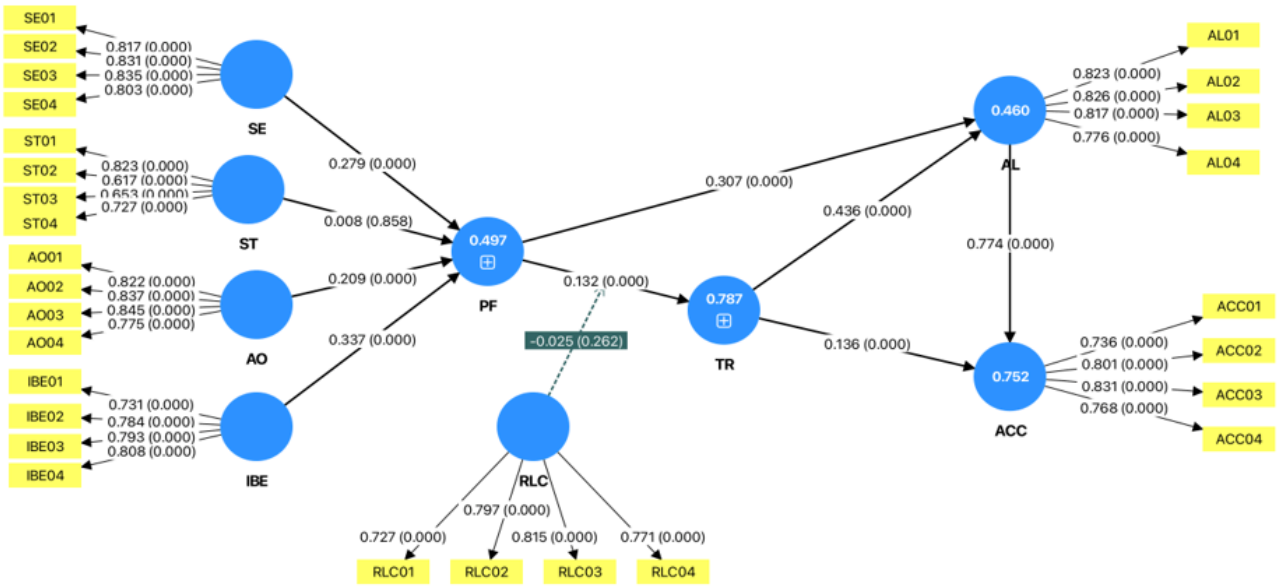


Figure 4

Hypothesis Testing Results (Direct Effects)

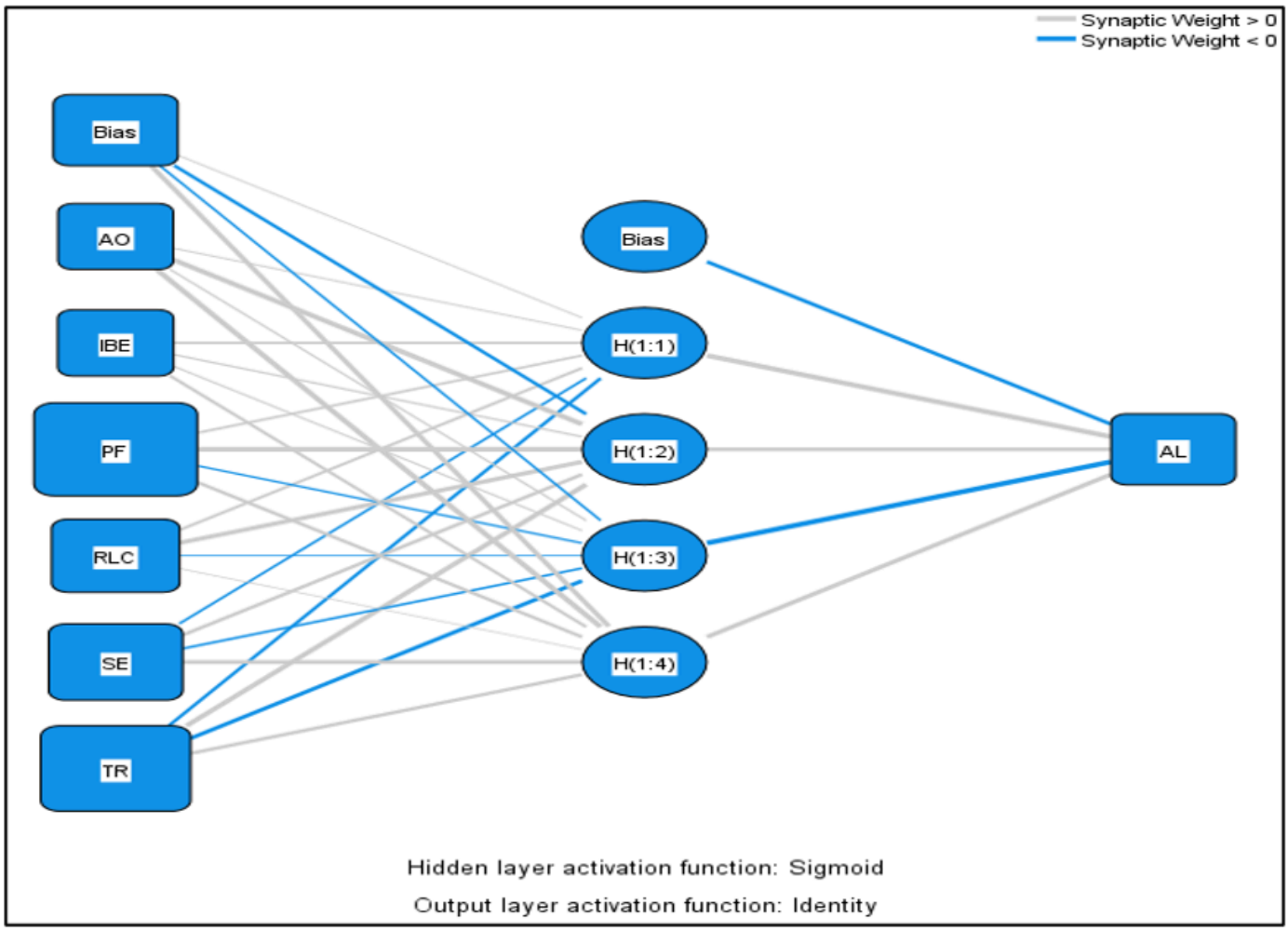


Figure 5

ANN model

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- Appendix.docx