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ANALYZING THE CONFLUENCE OF ALGORITHMIC TRANSPARENCY, ACCOUNTABILITY, AND DATA PRIVACY: A COMPREHENSIVE STUDY ON TRUST DYNAMICS IN AI SYSTEMS

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Abstract

The emergence of Artificial Intelligence (AI) systems across a range of fields has raised serious concerns about transparency, accountability, and data privacy. The purpose of this study is to address three important research gaps. First, there is a lack of research that empirically examines the simultaneous effects of Algorithmic Transparency (AT), Accountability Mechanisms (AM), and Data Privacy Policies (DPP) on Trust in AI Systems (TAS). Second, insufficient attention has been given to the role of DPP as a moderating factor between AT and TAS. Finally, the socio-cultural and institutional context—specifically the higher education and IT sectors in Turkey—has lacked applications of integrated Structural Equation Modeling–Partial Least Squares (SEM-PLS) approaches. This study is grounded in Social Cognitive Theory and surveys 398 participants, including university students and IT professionals. The findings indicate that AT, AM, and DPP are significant predictors of TAS, with DPP demonstrating a strong moderating effect on the relationship between AT and TAS. These results contribute theoretically by integrating three key components of ethical AI governance and offer practical implications for policymakers and practitioners aiming to foster trust in AI systems. The study underscores the necessity of developing transparent, accountable, and privacy-respecting frameworks to encourage societal acceptance and the ethical adoption of AI technologies.

Keywords: Artificial Intelligence, Trust, Algorithmic Transparency, Accountability, Data Privacy
JEL Classification: D83, C38, K38

ALGORİTMİK ŞEFFAFLIK, HESAP VEREBİLİRLİK VE VERİ GİZLİLİĞİNİN BİRLEŞİMİNİ ANALİZ ETMEK: YAPAY ZEKA SİSTEMLERİNDE GÜVEN DİNAMİKLERİ ÜZERİNE KAPSAMLI BİR ÇALIŞMA

Öz

Yapay Zekâ (YZ) sistemlerinin çeşitli alanlarda ortaya çıkışı, şeffaflık, hesap verebilirlik ve veri gizliliği konularında ciddi endişeleri gündeme getirmiştir. Bu çalışmanın amacı, üç önemli araştırma boşluğunu ele almaktır. İlk olarak, Algoritmik Şeffaflık (AŞ), Hesap Verebilirlik Mekanizmaları (HVM) ve Veri Gizliliği Politikalarının (VGP) Yapay Zekâ Sistemlerine Güven (YZS) üzerindeki eşzamanlı etkilerini ampirik olarak inceleyen çalışmaların yetersizliği bulunmaktadır. İkinci olarak, VGP'nin AŞ ile YZS arasındaki ilişkide düzenleyici (moderator) bir faktör olarak rolüne yeterince dikkat edilmemiştir. Son olarak, özellikle Türkiye'deki yükseköğretim ve bilişim sektörlerine özgü sosyo-kültürel ve kurumsal bağlamda, entegre Yapısal Eşitlik Modellemesi–Kısmi En Küçük Kareler (SEM-PLS) yaklaşımlarının uygulamalarına rastlanmamaktadır. Sosyal Bilişsel Teori temel alınarak yürütülen bu çalışmada, üniversite öğrencileri ve bilişim sektörü profesyonellerinden oluşan 398 katılımcı ile anket gerçekleştirilmiştir. Bulgular, AŞ, HVM ve VGP'nin YZS'nin önemli yordayıcıları olduğunu ve VGP'nin, AŞ ile YZS arasındaki ilişkide güçlü bir düzenleyici etkisi bulunduğunu göstermektedir. Bu sonuçlar, etik YZ yönetişiminin üç temel bileşenini entegre ederek kuramsal bir katkı sunmakta ve YZ sistemlerine güven inşa etmek isteyen politika yapıcılar ve uygulayıcılar için pratik çıkarımlar sağlamaktadır. Çalışma, toplumun YZ teknolojilerini benimsemesini ve etik şekilde kullanmasını teşvik etmek için şeffaf, hesap verebilir ve gizliliğe saygılı çerçevelerin geliştirilmesi gerekliliğinin altını çizmektedir.

Anahtar kelimeler: Yapay Zeka, Güven, Algoritmik Şeffaflık, Hesap Verebilirlik, Veri Gizliliği
JEL Sınıflaması: D83, C38, K38

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1. Introduction

Artificial Intelligence (AI) has the potential to change the way we work globally, across all sectors such as health care, commerce, communication, and security (Bughin, 2017; Doruköz & Uslu, 2023; Radanliev, 2025). Research by AGS Global in Turkey estimates AI and the Internet of Things could contribute approximately $15.7 trillion to the global economy by 2030, and that potential has increased the level of strategic attention Turkish companies are taking toward AI (AGS Global, 2023). However, AI technologies are evolving rapidly and the pace of that evolution poses important issues around transparency, accountability, and privacy. Research by TÜSİAD suggests that 88% of Turkish companies have stated that they are addressing the ethical and regulatory issues surrounding AI, but their awareness is largely one-dimensional and principally informational (A. Guastella & E. Seçkin, 2025).

Education is also affected by AI technologies. The Ministry of National Education in Turkey has created the "Department of Artificial Intelligence and Big Data Applications" under YEĞİTEK to help advance digital transformation in education. The aims of the department are to find AI-based Educational Applications, build pathways for their use, and to create resources and training for promoting AI literacy. The Ministry of National Education of Turkey (Milli Eğitim Bakanlığı, MEB) (MEB, 2025). At the level of higher education, reports created by The Council of Higher Education (Yükseköğretim Kurulu, YÖK) highlight the importance of universities being strategic in relation to AI technologies. They also note that university students and faculty members should receive education focused on AI to help prepare them for new labor markets. Further, emphasis was placed on starting new AI-based academic programs and updating existing curriculums (Savaş, 2021) (YÖK, 2025). Thus, students and academic staff in university-dense cities, like Sakarya, can improve their awareness and practical competencies in AI along with industry personnel. Given these actions there is a need for greater awareness and more definitive policies on ethical AI and data security.

The growing use of AI in higher education raises a number of important ethical and societal challenges: data privacy, algorithmic bias, and academic integrity, among others. While university students are aware that AI has the potential to transform education, few understand how to appropriately and ethically use it (Zouhaier Slimi & Beatriz Villarejo Carballido, 2023). Particularly related to the use of AI in personalized learning applications, these disciplines are likely to welcome ethical controversies tied to student privacy and data security (Meylani, 2024). Thus, higher education institutions need to start proactively developing policies and

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regulations that proactively consider accessibility, transparency, and ethical conduct in their use of AI in the educational space.

There is also a major difference in AI literacy among the faculty. The 2025 Global AI Faculty Survey indicates only 17% of academic staff regarded themselves as AI advanced or experts while the remainder, around 40%, identify themselves in the beginner or completely unfamiliar with the technology stage. This difference in understanding is a major barrier to the effective incorporation of AI into teaching and learning. Therefore, improving faculty opportunities in AI-related education and professional development should be seen as a strategic priority for universities in realization of their digital transformation objectives (Digital Education Council, 2025).

In this context, higher education institutions adopting inclusive, transparent and ethical practices, have been shown to enable the effective use of the opportunities provided by AI for student success and democratization of access to information (Abdurohman, 2025). Additionally, higher education ecosystems must introduce continual training programs for students and faculty members in regard to AI technologies which will create awareness and develop the right policies in education (AlDhaen, 2022).

The use of AI technologies in the academic, educational, and information technology sectors in Turkey has raised ethical and data privacy issues. The lack of Algorithmic Transparency (AT) is one major issue that leads to a loss of user trust and serious ethical concerns. According to the Turkish Personal Data Protection Authority (Personal Data Protection Authority [KVKK], 2025), AI systems should be described transparently and be accountable if any explainable and auditable decision making is demonstrated (Personal Data Protection Authority, 2025). Accordingly, without proper accountability, it can be difficult to establish who is responsible when a poor decision is made by an AI system. The Turkish Informatics Association states that proper accountability for AI applications requires the establishment of internal and external auditing mechanisms (Turkish Informatics Association, 2023).

Data privacy continues to be one of the most problematic aspects of AI deployment. The quantity of data that AI systems require is huge and raises serious alarms regarding personal data privacy. The widespread usage of AI tools, according to KVKK, has also become a growing concern regarding data privacy and could violate individual rights of privacy (Personal Data Protection Authority, 2025). Thus, using AI tools in Turkey effectively and ethically must also

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include constructive policies regarding transparency, accountability, and data protection, in order to build people's trust and ensure sustainable AI practices in critical sectors (Asıl, 2025).

Trust in Artificial Intelligence Systems (TAS) is a crucial factor for the successful acceptance and use of these technologies. Recent empirical research studies conducted in Turkey found that trust levels among university students, academic staff, and professionals working in the Information Technology (IT) sector depend on how trustworthy they perceive the transparency, explainability, and ethicality features of the AI systems. In educational and technology-related contexts, trust is an especially significant influencer of users' willingness to engage with AI-related tools (Hosain et al., 2023; Altuntaş & Karabay, 2024; Vakifli, 2025).

Mayer, Davis, and Schoorman developed a theoretical foundation for trust in 1995 in their paper "An Integrative Model of Organizational Trust". This foundational model has been imported into a technological realm in which trust plays an important role, including for AI, suggesting that trust emerges from the users' perceptions of its ability, benevolence, and integrity (Mayer et al., 1995). Within Turkish contexts, this model has been particularly relevant in digital education systems, online assessments, hybrid modern management systems, and AI-enabled academic advising, where all trust played a key role in the potential for engagement by users. Therefore, for the AI technologies to be able to achieve a sustainable embedding into the higher education and IT industries in Turkey, the strategies must consider explainability, ethical frameworks, and accountability frameworks that promote trust.

Trust in AI systems (TAS) is a common touchpoint among many distinctive elements of AI systems; that is, issues surrounding transparency, accountability, and data privacy. In the case of Turkey, the relationship between trust in AI systems (TAS) and the level of understanding of the workings of algorithmic decision-making, yielded a mix of value and potential harm to university student, academic staff, and IT employees (Omrani et al., 2022). The absence of appropriate AT typically is generated into uncertainty regarding decision-making, infinite trust. This universal absence of transparency would appear to be inconsistent with Burrell's (2016) work, 'How the Machine 'Thinks', which explains how algorithmic opacity can undesirably create bad outcomes identified through how users designate trust and persuasive credibility (Burrell, 2016). Finally, the presence or absence of accountability mechanisms (AM) has some influence of trust. User only had evidence of potential conceptions that formal accountability was exposed to rights to remedy, a judicial proceeding, or oversight would result in robust trust in the AI system (Shin, 2020). This tells use that advanced and data centric cities like Sakarya has to undertake AI use cases that are based upon standardized procedures regarding

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transparency and accountability in order to design trusted experiences and rendered AI technological advancement sustainable in higher education delivery and IT.

Besides the ideas of transparency and accountability, data privacy is tied to the notion of user trust. Evidence suggests that the level of transparency, accessibility, and usability of an AI system's data privacy protocols influences users' willingness to share personal information with a system. Recent findings from Turkey suggest that 64% of users feel concern for dealing with their personal data while interacting with AI technologies (EY Türkiye, 2025).

Educational institutions are aware that adequate data governance policies and practices help ensure the secure use of sensitive data related to both students and faculty. Generally, the data collected by the institutions is based on students and facilitators using online assessment systems, learning management systems, and academic analytics systems. As AI applications become more prevalent in the educational sphere, anxiety over what and how data is collected, stored, and shared could cause an irreparable loss of trust. The fear experienced by practitioners in the IT profession is similarly observed, where unauthorized data movement or misuse sustain beliefs in privacy and impacts on professional vulnerability (Yang & Beil, 2024). Transparency is an important factor in establishing TAS. When users understand the logic behind algorithmic decisions, their overall experience with technology improves and ethical and responsible use is more likely to occur as well (Schmidt et al., 2020). In urban areas, like Sakarya, the adoption of AI in many sectors is creating a new social landscape and within that, the establishment of transparent, user-specific, and compliant Data Privacy Policies (DPP) are imperative to support trust by the public in AI.

In academic contexts, the openness of automated grading algorithms engendered the perception of justice and impartiality by students, making it more convenient for teachers to justify academic integrity of results (Gustilo et al., 2024). With regard to healthcare applications, the transparency of the basis for AI-generated diagnostic recommendations has been shown to improve user acceptance and satisfaction for patients (Ali et al., 2023). This is consistent with research conducted by Grimmelikhuijsen (2022) on the topic of “AT”, which suggests that AI systems with an easily explainable decision making resulted in much higher user trust and recommendations (Grimmelikhuijsen & Meijer, 2022). The use of interpretable AI inspired greater confidence, and informed the ethical deployment of technology in both institutional and workplace contexts.

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Additionally, to transparency, accountability has been recognized to be a critical factor in users' TAS. Transparency can help people understand how choices are being made (if they are made), whilst accountability builds users' trust by providing guarantees that systems may be challenged and errors resolved (Herdiani et al., 2024). The academic literature in Turkey stresses the importance of such mechanisms, especially in educational AI, such as automated grading systems, and IT sector, such as recommendation engines (Yeşilyurt et al., 2024). This view is supported by Kim and Routledge's (2022) research on algorithmic decision-making, revealing users have much greater trust when they understand that a system can be fixed, appealed or redressed (Kim & Routledge, 2022). Similarly, in Turkey, some university-level management systems have adopted some feedback modules that allow students to address their concerns about, or appeal their grades, send messages to advisors, as well as allow users to evaluate AI's suggestions, engendering trust in the system. Achieving transparency is clearly a basic requirement, but is not enough on its own. AI uses need to intentionally have structured mechanisms of accountability for users to express their concerns and rectify any mistakes. These kinds of structures offer a more balanced and trustworthy relationship between users and systems, and therefore offer more opportunity for long-standing acceptance and ethical use.

A significant amount of existing user TAS literature tends to emphasize either specific technical areas or more broad ethical areas. These exceptions are valuable, but there is also a missing piece of literature that indicates the relationship of AT, AM and DPP on user trust. Again, the use of AI should be driven by more than just the technical features, it’s about an integrated architecture of ethical accountability and user-centered design that should come together.

This study will fill that gap and make an original contribution. Prior studies may have only relied on qualitative interviews or case-based design for a methodology, and this study utilized Structural Equation Modeling (SEM) with SMART-PLS to take a systematic look at user trust from the perspective of the three areas. It allows for a rigorous statistical analysis to derive research findings that is more statistical empirical validity, and to enable deconstructing construct importance and interaction and each level that contributes to trust. The conceptual basis of this is interdisciplinary in nature, blending from application areas of computer science, law, and social psychology which offers broad analytical footing for them and others seeking to study digital transformation of education, data protections governance, and technological trust mechanisms. This alignment provides for more converging approach to view user confidence across social domains of AI.

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This study's findings reveal a statistically significant and strong positive relationship between AT and user trust, supporting the claims put forth by Tsamados et al. (2021) empirically (Tsamados et al., 2022). Additionally, the findings of this study confirm the theoretical claims of Adadi and Berrada (2018) by identifying AM as strong predictors for trust (Adadi & Berrada, 2018). Interestingly, DPP exerted a more complex influence. While DPP were not universally impactful, they mattered to users who had preexisting knowledge of AI; meaning, we can also consider data privacy as a moderating variable in our model on user trust. Overall, this study highlights the relevance of context and experience with AI in influencing user trust.

This research utilizes an empirical study to extend knowledge as to how the merging of AI, accountability, and data privacy influences user trust; while also integrating a thorough manner to fill the gaps present in past studies. The complete findings contribute to academic study contributions to knowledge and contribute to policy making in the legislative context. There are clear pathways to reimagine legislation and regulations since current legislation and regulations need to be amended and incorporate language related to the transparency and accountability of algorithm operations. The global economic case for AI also provides avenues towards evaluating the global economic case from a more ethical, inclusive and sustainable perspective. From the practitioners view, the findings also indicate strategic opportunities. For example, transparency within algorithms can be marketed as a Unique Selling Proposition (USP) and structured accountability mechanism could be used as a means of reducing user risk. Ultimately, engaging users and maintaining trust be user-friendly DPP has also emerged as an effective way of both maintaining trust and expanding market.

2. Literature Review

For the last twenty years, user trust has been a central tenet for a successful implementation and adoption of new technology-based innovations. When it comes to technological systems, including AI, user trust is a multi-dimensional variable warranted attention. Mayer, Davis and Schoorman’s (1995) seminal trust model has served as the ground upon which trust research for a variety of AI applications was developed and reiterated that user trust is not simply an important psychological construct, but an important facilitator for ethical and effective use of AI (Kruse et al., 2019; Michael et al., 2019). With AI starting to permeate almost every industry, including education, healthcare, public services and information technologies, the notion of trust is expanding to incorporate not only technical manifestations of trust in digital technology, but societal manifestations.

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In the National Artificial Intelligence Strategy of Turkey 2021–2025, released by the Republic of Türkiye Ministry of Industry and Technology, one of the goals is for AI systems to contribute up to 5% to Turkey's GDP by 2025. This goal will only be achieved if ethical and trust-based infrastructures are put in place to encourage societal acceptance (Republic of Türkiye Ministry of Industry and Technology, 2021). Although Edelman's 2022 Global Trust Barometer states that only 49% of respondents trust AI systems (Edelman, 2022), local research conducted in Sakarya shows skepticism towards AI is prevalent among university students and IT sector professionals. Therefore, to foster user trust, we will not only focus on technical efficiency but also on transparent, accountable, and ethical system design.

User TAS is not just a technical issue it's a behavioral and social issue that determines whether users are willing to share data, act on AI-informed recommendations, and champion the inclusion of AI in their ecosystems (Sharma et al., 2022). Overall, the level of user trust in an AI system is directly correlated with user engagement, acceptance of the AI system outputs, and a willingness to share data freely or collaborate and support the AI system's success. Trust is central in the context of education and information technology, is an important enabler of human-AI interactions and the adoption of AI-influenced human decision-making at the social level.

The literature on individual pieces of the trust puzzle (like AT, AM, and DPP) is useful, but it generally does not provide a cumulative understanding on how these pieces interact to influence TAS (Robinson, 2020; Sharma et al., 2022). Most studies address such pieces separately, or times only look at one piece of the puzzle at a time without considering their interrelationships. In this perspective, realizing the economic value of AI will require a strong trust infrastructure which can be created not only through legislation, but also through systems that are transparent, accountable and user-focused (Thiebes et al., 2021).

For example, the work by Tsamados et al. (2021) on AT, and Adadi and Berrada's (2018) piece on accountability in AI systems highlight important insights into trust. In practice, however, both contributions rarely intersect or offer any insights into the joint relationship between transparency and accountability on levels of trust. The literature has explored, as a second category, the notion of data privacy (Adadi & Berrada, 2018), yet even in this case, authors have largely not contemplated data privacy as a possible moderating variable that could impact the relationship between AT, accountability and user trust.

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The literature gap is, therefore, apparent: there has been little research blending the three important aspects - transparency, accountability and data privacy - to demonstrate a composite impact on TAS. Above all, there are no studies which map the complex and multidimensional interrelations between these aspects, nor have the potential moderating or mediating effects of DPP been researched (Tsamados et al., 2022). This gap in the literature is evident in Turkey-specific research, where studies focus on data security, transparency or another separate variable, and not the combination of these aspects in terms of user trust. In other words, these issues of transparency, accountability and data privacy, and their relationship to trust, are important to understand for certain user groups, such as professionals in education and the information technology sector from multiple perspectives theoretically and practically. Thus, it is important to conduct empirical research that examines the influence of each component separately as well as the transparent and collaborative manner, which impacts trust in AI systems (Thiebes et al., 2021).

With all of this, the problem statement can thus be stated as: "How do algorithm transparency, AM, and DPP collectively and dynamically affect TAS's; and can we translate that understanding into meaningful ways to influence in practice and in policy?"

It is clear that the identified literature gap is worth focusing on: there is limited research that integrates AT, accountability, and data privacy into one analytic set of dimensions to examine their combined impact on trust in AI's. Overall, most of the existing research tests these variables aside from each other and does consider how the multidimensional, intricate relationships may influence user trust. It makes progress on both theoretical and practical frontiers increasingly difficult to scale, particularly in instances where TAS matters for success in the long term. DPP has not been investigated if it moderated, or mediated the relationship between Algorithm Transparency and Data Accountability, where each directs trust. Examples of how users feel secure in their data may raise or lower their trust even more. Future research can invoke multilevel, but not single tradition models, but study these three aspects all together to realize a complete understanding of the factors that lead to trust in AI.

With this conceptual grounding, our research study could articulate the problem statement as follows: "To what degree do algorithmic transparency, accountability, and data privacy present independently pursuing, beyond their colocation at varying levels of interplay, and how can enhance knowledge of that interplay produce outcomes that can lead to evidence informed policy and practice?" This problem statement answer the multi cues that are evident in the

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literature, and accentuates the need for a integrated assessment of the technical and ethical aspects of determining trust in AI type settings.

2.1. Theory: Social Cognitive Theory

Social Cognitive Theory (SCT), originally developed by Bandura (1986), argues that learning occurs in a social context where there is reciprocal interaction between person, environment, and behavior (Azza Alomary & John Woollard, 2015). SCT also emphasizes self-efficacy, or belief in one's capabilities to organize and execute the course of action required for producing given levels of performance. SCT offers a psychological view for examining TAS's.

It emphasizes that trust is not solely an individual's cognitive calculation, but it is shaped by social and systemic external factors. As a result, the social context in which AI is situated, the AI systems behaviors, and the individual's attitudes and beliefs towards the AI will interact reciprocally and with these various contexts (Azza Alomary & John Woollard, 2015; Malik & Budhwar, 2023). In SCT, transparency is handled as a transparent social context in which the AI system will operate.

Accountability relates to the behavior of the AI or if it is behaving in a socially acceptable and ethical way, whereas data privacy is under the environment or behavior categories since it affects how the user can control their own information, and thereby affects their feelings of self-efficacy and trust (Malik & Budhwar, 2023; McLeod & Dolezel, 2022). Reciprocal Determinism: SCT's idea of reciprocal determinism indicates that transparency, accountability, and data privacy are all interrelated factors affecting trust, and are not mutually exclusive. Behavioral Capability: In SCT, understanding a behavior and enacting it improves the capability. That is if users understand how ai works (transparency) and how it is accountable, they are more likely to trust it. Self-Efficacy: The more obvious the DPP, the more in control the user feels, which should, in turn, increase self-efficacy and trust. Based on SCT, social environment transparency leads to increased behavioral capability, and trust. Moreover, SCT describes that adherence to norms improves trust; thus, accountability techniques which have ethical AI behavior should improve trust (Knowles & Richards, 2021; Novelli et al., 2024). Moreover, the construct of self-efficacy in SCT propounds that clarity in data control will promote trust. Finally, the construct of self-efficacy in SCT propounds that clarity in data control will promote trust.

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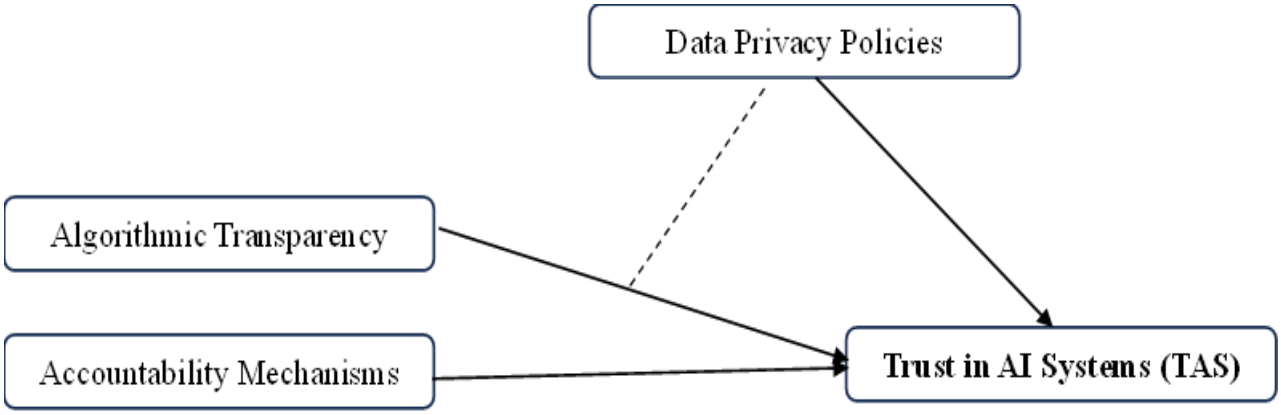
Hypotheses development

1. **H1**: Algorithmic Transparency positively related to Trust in AI Systems.
2. **H2**: Accountability Mechanisms are positively related to Trust in AI Systems.
3. **H3**: Data Privacy Policies are positively related to Trust in AI Systems.
4. **H4**: Data Privacy Policies moderate the relationship between Algorithmic Transparency and Trust in AI Systems.

Figure 1. Conceptual framework



SCT's concept of reciprocal determinism suggests that the impact of transparency on trust will be stronger when users feel they have control over their data.

3. Method

This research used a quantitative research design, which is recognized as generating reliable and generalizable findings in social science research (Creswell & Creswell, 2018; Bryman, 2016). Quantitative methods were appropriate for this research since they allow for the testing of hypotheses and examination of relationships among variables with replicable and structured procedures. The survey instrument was administered to 398 individuals and employed Likert-scale questions based on AT, AM, DPP, and TAS. The data collected from the survey were analyzed using Structural Equation Modeling (SEM) with SMART-PLS software, an appropriate software for examining theoretical models that include multiple latent constructs (Hair et al., 2019; Hair et al., 2021) . This design will allow the research to be statistically sound and replicable, providing empirical support to the understanding of trust in AI systems.

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3.1. Method of Data Collection

The data collection for this study was undertaken using a structured online survey instrument designed to capture participants' views on AT, AM, DPP, and TAS. Respondents completed items on a five-point Likert scale (1 = strongly disagree; 5 = strongly agree). Prior to full deployment, the instrument underwent a pilot test with a small group to assess clarity and reliability. The study adhered to ethical policies and informed consent procedures to protect participants' privacy and confidentiality.

3.2. Description of the Dataset

The online survey was administered via a secure and anonymous platform to ensure participant confidentiality while maximizing reach to a diverse and geographically dispersed population. Prior research supports online data collection as a means to reduce participation barriers, access heterogeneous samples, and improve response accuracy by allowing participants to respond in a comfortable private setting (Wright, 2005; Evans & Mathur, 2018). The online format enabled completion at respondents' convenience during the data-collection window, thereby reducing response burden and supporting participation rates. Participants were purposively targeted to obtain variability in AI experience and engagement, enhancing the external validity and generalizability of findings for studies of trust in emerging technologies (Hair et al., 2019). Table 1 summarizes the sample's demographics.

As shown in Table 1., the vast majority of our respondents (56.5%) were university students while the other (43.5%) had jobs in some area of information technology. As well, the gender breakdown was fairly even with 49.7% male and 50.3 % female. In terms of ages, the breakdown also indicated that the majority of respondents were aged 18-30 (42.2%) which represented an especially strong group of younger individuals who will likely use AI technologies in their future careers. The demographics showed a diversity of perspectives on algorithmic transparency and accountability mechanisms regarding data privacy policy issues. On the contrary, they also provided the opportunity for subgroup analysis and help to determine that SEM (Structural Equation Modeling) results can also be generalized across these groups in the population.

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Table 1. Descriptive statistics of respondents

Variables	Frequency	Percentage (%)
Gender		
• Male	198	49.7
• Female	200	50.3
Age Group		
• 18-30	168	42.2
• 31-45	130	32.7
• 46+	100	25.1
Familiarity with AI		
• Low	100	25.1
• Moderate	198	49.7
• High	100	25.1

To assess potential non-response bias, we conducted Levene's test for equality of variances, a standard procedure to evaluate variance homogeneity across subgroups (Levene, 1960; Field, 2018). We compared variance across four contrasts—response mode (email vs. post), firm size (small vs. large), age (18–30 vs. 46+), and AI familiarity (low vs. high). In all cases, $p > .05$, indicating no significant variance differences and reducing concern about non-response bias (Hair et al., 2019, 2021). Detailed results are presented in Table 2.

Table 2. Distribution techniques and procedures utilized in the study's data collection Process

Group	Levene's Statistic	P-value	Conclusion
Email vs Post	1.25	0.27	No significant difference
Firm Characteristics: Small vs Large	0.86	0.36	No significant difference
Age Group: 18-30 vs 46+	2.01	0.16	No significant difference
Familiarity with AI: Low vs High	0.97	0.33	No significant difference

3.3. Sampling Method and Data Handling

The final analytic sample comprised 398 participants, drawn from Turkey's higher education and IT sectors, reflecting a broad spectrum of AI experience and engagement. Data were collected over a four-week period (January–February 2025) via an online questionnaire distributed through institutional mailing lists and professional networks. A stratified random sampling strategy was employed to ensure balanced representation across gender, age, and AI familiarity strata. Prior to analysis, the dataset was screened for missing values and outliers: missing data were handled via listwise deletion, and outliers were identified using standardized

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z-scores ($|z| > 3$) and removed to enhance the robustness of subsequent statistical analyses. Table 1 reports the demographic composition of the sample.

4. Findings and Discussion

Common Method Bias (CMB) is a concern in survey-based studies, as it refers to the variance attributed to the measurement method rather than the constructs the study aims to assess. This bias can artificially inflate or deflate relationships between variables. To mitigate this issue, several tests can be applied, such as Harman's Single Factor Test, Confirmatory Factor Analysis (CFA), or Marker Variable Techniques (Kock et al., 2021). In this study, the most appropriate method considered is the Harman's Single Factor Test due to its ease of implementation and widespread acceptance in the field.

Table 3. Harman's single factor test table

Factor	Eigenvalue	Variance Explained (%)
Factor 1 (Common Method Factor)	1.80	18
Factor 2	2.70	27
Factor 3	1.50	15

The results in Table 3., suggest that the first factor explains 18% of the variance, which is below the concerning threshold of 50%. Thus, Common Method Bias is unlikely to significantly affect the study's conclusions.

This section will explicitly define and operationally define the constructs relevant to the research model, in order to offer a consistent application; different accounts will have different uses, but standardisation will provide a consistent way to measure these constructs meaningfully. The project is comprehensive on Table 4., where to offer a complete description of the conceptual definition of each construct as well as those mostly methodological items: sources, the measurement items, and the scale formats. The structured way in which the research outcomes were reporting helps ensure consistency in how latent variables are accurately characterised and quantified. By offering transparency and reproducibility about the measurement approach, confidence can be engendered for users to scrutinise and reproduce the findings of the study through their application of the same measurement approach. Similar, when the construct definitions can be aligned with standards from the literature, upon which their definitions have been constructed and have existed along an empirical minefield of academic literature, the theoretical foundation for the research is strengthened to ensure the

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measured variables are capturing the intended psychological and behavioural aspects of trust, transparency, accountability, and data privacy in AI systems.

Table 4. Operational definitions and measurement instruments of research constructs

Construct	Definition	Measurement Scale
Algorithmic Transparency	The extent to which the functioning of the AI system is clear and understandable	Likert Scale (1=Strongly Disagree, 5=Strongly Agree)
Accountability Mechanisms	Systems in place to hold the AI accountable for its decisions and actions	Likert Scale (1=Strongly Disagree, 5=Strongly Agree)
Data Privacy Policies	Rules governing the use and storage of user data	Likert Scale (1=Strongly Disagree, 5=Strongly Agree)
Trust in AI Systems	Level of trust users have in the AI system	Likert Scale (1=Strongly Disagree, 5=Strongly Agree)

For the measurement of the constructs, the Likert Scale is used to measure the breadth and depth of respondents' attitudes to different elements of AI. This type of measurement instrument is prevalent in the research literature, allowing researchers to easily compare attitudes and perceptions while providing a strong set of data that is rich in information. The definitions of both constructs are aligned with the literature, thus building on the current research knowledge and scholarship. As the constructs are inherently subjective, for the purposes of this study, the Likert scale represents the most relevant and nuanced measure.

4.1. Pretest Results and Discussion

The goal of the pretest was to confirm the plausibility and applicability of the items in the questionnaire. It was undertaken with a sample of 30 people fitting the profile of the population of interest in the main study. The factor loading for each construct is above the minimum value of 0.7 indicated that the items have high convergent validity (Sarstedt et al., 2019, 2020; T. Ramayah et al., 2017). The means and standard deviations suggest a good spread of responses, confirming that the items were capturing variance in respondents' opinions (Table 5.).

Table 5. Preliminary assessment outcomes of measurement instruments

Item	Mean	Standard Deviation	Factor Loading
Algorithmic Transparency	3.5	0.76	0.82
Accountability Mechanisms	4.1	0.67	0.88
Data Privacy Policies	3.8	0.59	0.85
Trust in AI Systems	2.9	0.79	0.79

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The pilot test was enforced with 50 individuals. The Cronbach's Alpha values were at least 0.7 for each construct demonstrating the items are internally consistent. The factor loading ranges were also substantial demonstrating that the constructs are well established and salient for the study (Mikalef & Pateli, 2017; Sarstedt et al., 2019; T. Ramayah et al., 2017). Based on this evidence, the measures in the questionnaire can be determined to be reliable and valid for the main study. The means and standard deviations corroborate with the idea that the items are well calibrated to account for the variability of people's responses, this finding adds validity to the findings of the research. With both the pretest and pilot test, it has been confirmed that the questionnaire was a fit to use in the research and it time to move into the first stage of data collection (Table 6.).

Table 6. Preliminary validation results from pilot testing phase

Constructs	Cronbach's Alpha (α)	Means (SD)	Factor Loading Range
Algorithmic Transparency	0.85	3.5 (0.76)	0.81- 0.85
Accountability Mechanisms	0.88	4.1 (0.67)	0.86- 0.90
Data Privacy Policies	0.87	3.8 (0.59)	0.83- 0.88
Trust in AI Systems	0.81	2.9 (0.79)	0.77- 0.82

4.2. Reliability and Convergent Validity Assessment

Reliability refers to the consistency or repeatability of measurements. One common method to assess reliability is to compute Cronbach's Alpha (α). In this study, all constructs exhibited Cronbach's Alpha values above the generally accepted threshold of 0.7. Specifically, AT showed an α of 0.85, AM had an α of 0.88, DPP were at 0.87, and TAS registered an α of 0.81 (Hair et al., 2019, 2021; T. Ramayah et al., 2017). These high alpha values confirm that the items within each construct are internally consistent and reliable.

Convergent Validity refers to the extent to which indicators of the same construct correlate positively and highly with one another. A commonly used rule of thumb used to determine if there is adequate convergent validity is to examine the factor loadings (which should be above 0.7). In our case, all of the factor loadings were above 0.7, and ranged from 0.77 to 0.90 across all of the constructs (Christian M. Ringle et al., 2015; Henseler et al., 2014; T. Ramayah et al., 2017). The high correlations among indicators of the same construct provides us with very good evidence of convergent validity.

In addition to looking at the factor loadings, we also wanted to examine the Average Variance Extracted (AVE) values for each construct. All of the values we were above the commonly used

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lower art limit of 0.5 that indicates that more than 50% of the variance explains the construct and that any variation left is due to error (Hair et al., 2019, 2021).

Table 7. Reliability and convergent validity metrics of measurement constructs

Constructs	Cronbach's Alpha (α)	Factor Loading Range	AVE
Algorithmic Transparency	0.85	0.81- 0.85	0.72
Accountability Mechanisms	0.88	0.86- 0.90	0.75
Data Privacy Policies	0.87	0.83- 0.88	0.73
Trust in AI Systems	0.81	0.77- 0.82	0.62

To sum up, the validity of convergent and reliability of these constructs were affirmed in what was presented in Table 7. All Average Variance Extracted (AVE) values surpass the recommended value of 0.50 position by Fornell and Larcker (1981) proving that the constructs explain more than 50% of the variance on their respective indicators. This finding support the hypotheses whereby the measurement items are indeed associated with the latent variables. Further, all Composite Reliability (CR) values were found to be above the acceptable level of 0.70 (Hair et al., 2019) further reinforcing the internal consistency of scales used in the study. Overall, the results lend strong support for convergent validity of the measurement model meaning this design has strong methodological rigor, which means this design can be considered as a reliable basis for theoretical and practical implications.

4.3. Discriminant Validity Assessment

Discriminant validity is an important, and meaningful, part of construct validity, which is defined as the extent to which a construct is actually different from other constructs in a model. Discriminant validity must be established to demonstrate that the measurement items from different constructs do not overlap too much, as well as, to verify that each construct also has a unique variance that is not shared with other constructs. Discriminant validity was determined in this study using several indicators to present strong evidence for construct distinctiveness (T. Ramayah et al., 2017).

Methods of testing discriminant validity include: the Fornell-Larcker criterion, where you compare the square root of the Average Variance Extracted (AVE) of each construct to the correlations with the other constructs, to see whether the square root of the AVE of each construct was larger than the correlations with other constructs; the Heterotrait-Monotrait ratio of correlations (HTMT), which provides a stricter test of discriminant validity and is the approach adopted by this study; and finally, other complementary validation techniques

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(thereby ensuring that the measures for the construct were distinct both theoretically and empirically). The Fornell-Larcker condition was met because every square root of the AVE was larger than every corresponding inter-construct correlation. The HTMT values were all less than the conservative cutoff of 0.85. These findings support the discriminant validity as evidenced in Table 8. Of course this study adhered to, and exceeded, the minimum requirement for discriminant validity. The preceding tests of discriminant validity further limit the threat of construct redundancy and measurement, which potentially undermines the explanatory power of the structural model. The missing step of the above evaluation process is in the presentations and the assemblage of procedures to collaboratively validate constructs and measures (the essence of distinctness). Therefore, with this assemblage of evidence and other valuable contributions, it should help strengthen the research, build credibility and make researchers of all levels and experience more confident in the interpretations of the relationships between constructs in the present study (Christian M. Ringle et al., 2015; Henseler et al., 2014).

It should be noted that for complex models with latent variables, it is also very important to develop clear discriminant validity-especially if the relationship between the constructs is practically associated, but empirically distinct. The desired uniqueness is useful as it allows better parameter estimation and a better understanding of the kinds of causal mechanisms involved. The use of many validity measures is considered a best practice amongst quantitative methods and is beginning to be accepted as a standard of methodological diversity.

Table 8. Assessment of discriminant validity using Fornell-Larcker Criterion and HTMT ratios

Constructs	Algorithmic Transparency	Accountability Mechanisms	Data Privacy Policies	Trust in AI Systems
Algorithmic Transparency	0.85	0.60	0.52	0.49
Accountability Mechanisms	0.60	0.87	0.55	0.48
Data Privacy Policies	0.52	0.55	0.85	0.50
Trust in AI Systems	0.49	0.48	0.50	0.78

Note: Please note that the diagonal (bold) numbers are the square root of AVE for each construct, while the off-diagonal numbers are the correlations between constructs.

The diagonal (square root of AVE values) elements for each construct are larger than their corresponding off-diagonal elements in the same row and column, which are the correlations with other constructs, which establishes evidence of discriminant validity and supports the conclusion that each construct is different from the other constructs.

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5. Measurement and Structural Model Results

The measurement model explains how well the observed variables represent each of the latent constructs. Again, we determined our model has good reliability, convergent validity, and discriminant validity, therefore, we have sufficient measurement of each construct. There is also a structural model, which explains the relationships between the constructs. Though we have focused on the measurement model as part of our investigation, the structural model will be assessed with path coefficients, significance levels, and R-squared values to assess the relationships between the constructs (T. Ramayah et al., 2017; Wahyuni et al., 2019). In conclusion we have evidence of a strong measurement model, and a meaningful analysis of the structural model is possible. This contributes to our understanding of how AT, AM, and DPP influence stakeholders' trust in AI systems. Since we have strong evidence of discriminant validity in our study, we can have even more confidence in our construct distinctions, and the credibility and generalizability of our research.

The first hypothesis (H1) proposes that AT positively influences TAS. Greater transparency in algorithms is expected to increase user understanding and confidence, thereby fostering higher levels of trust in AI technologies. This hypothesis explores the important role of AT in generating user trust in AI systems. The data indicates a significant positive association between AT and trust in AI systems. The positive association further supports SCT as it is well-documented that transparency increases behavioral capability, and thus trust. AT is related to the extent and understandability of the AI decision-making processes are made available to end users. The data from the study reveals a strong statistically significant positive effect of perceived transparency on trust, which supports theoretical assertions that transparency reduces uncertainty and perceived risk associated with AI technologies. Transparency reduces uncertainty and perceived risk associated with AI technologies because it enables users to understand the logic and rationale associated with AI outputs. Transparency informs users' perceptions of fairness, reliability, accountability; reinforcing the trust base to enable productive human-AI collaborations. This finding elaborates upon and supports existing literature that identifies transparency as a fundamental precursor to trust in complex, opaque algorithmic contexts. Policy makers could implement regulations requiring AI companies to disclose their algorithms to foster trust.

The second hypothesis (H2) posits that AM have a positive impact on TAS. When clear mechanisms for responsibility and oversight are in place, users are more likely to perceive AI systems as reliable and trustworthy. The current hypothesis looks at the effect of AM formal

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structures, policies, and practices that encompass designs to ensure citizens are responsible and accountable on trust in AI systems. A positive relationship has been found between AM and trust in AI systems, which is consistent with the basic tenets of Social Cognitive Theory (SCT) adherence to certain behavioural norms promotes trust. The findings from the study demonstrate that overt AM practices substantially increase user trust, demonstrating their role in providing assurance for users that AI behaviours are being monitored and are auditable should they need to take corrective action. AM's serve as critical governance mechanisms closing the gap between autonomous system behaviours and human ethical standards allowing the stakeholders to hold AI systems responsible for the decisions and effects of their decisions. This improved perception of accountability has been shown to decrease user distrust while simultaneously increasing transparency and ethical adherence—leading to longer term trust development. This finding aligns with emerging frameworks of governance that emphasize accountability as a key element of responsible AI use. In order to repair trust in AI systems, public governing bodies could also develop standards around accountability in AI.

The third hypothesis (H3) suggests that DPP positively affect TAS. Strong privacy protections are anticipated to reduce user concerns about data misuse, thereby strengthening trust in AI systems. This hypothesis elaborates on the important role of DPPs in users' trust on AI applications. There was a moderate but meaningful moderation of the DPP on trust in AI system. This is consistent with the SCT construct of self-efficacy, in which lower path models of trust were possible when individuals had difficulty understanding how their data was controlled. Users cannot underestimate the role of well-positioned privacy policies that firmly control personal data and align with ethically and morally appropriate means to develop confidence in data users who are concerned about data misuse. The analysis confirms a positive and meaningful relationship between organized data privacy practices within an organization and increased levels of trust, and fundamentally, protecting user data is a pillar in adopting ethical AI practices. By providing transparency in an organization's data practices, a DPP ensures either explicit or implicit consent, or endorses regulatory compliance, users develop positive experiences around privacy protection which enhances perceptions of trust. This finding is consistent with a large number of studies that recognized privacy protection as a foundational aspect of an ethically and responsibly designed trustful AI ecosystem. Organizations are encouraged to create written explicit and detailed DPPs to facilitate trust.

The fourth hypothesis (H4) proposes that DPP moderate the relationship between AT and TAS. In other words, the positive effect of AT on trust is expected to be stronger when robust privacy

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policies are in place. The current hypothesis investigates the moderating role of data privacy policies in the relationship between algorithmic transparency and trust. The current research found a significant moderating effect of DPP on the positive effect of AT on trust in AI systems. The relationship provides further evidence for the idea that SCT functions on a principle of reciprocal determinism. Thus, the effect of AT on user trust is stronger when users believe they have control over their data. The results show that strong data privacy policies can enhance the positive relationship between transparency and trust. This reflects a synergistic interaction whereby privacy assurances significantly amplify the validity of transparent AI processes. This moderating relationship also suggests that authenticity and credibility, while important, may still be insufficient on their own to generate complete user trust except in the presence of robust privacy assurances. It has been shown that users are more likely to trust those AI systems that not only visibly state their processes, but also protect the user's data more vigorously thereby addressing both informational and security concerns. This integrative perspective supports the need to develop AI governance frameworks that combine and address both transparency and privacy to facilitate trustworthiness and user acceptance. AI systems need to operate transparently and disclose a degree of data control to users.

These findings illuminate several implications for policy-makers and practitioners alike. They provide empirical evidence for the significance of AT, AM, and privacy policies for enhancing trust in AI systems, all of which are witnessed in the various wells of SCT. This signifies a need to establish standardizing laws that force organizations to adopt trust-enhancing technology features. There is a genuine chance with this change to hasten the ethical use and uptake of value-added AI technologies while achieving socio-economic purposes at both micro and macro levels. As illustrated in Figure 2., synthesizes these relationships, providing a comprehensive framework that highlights how these elements collectively foster trust and guide ethical AI adoption.

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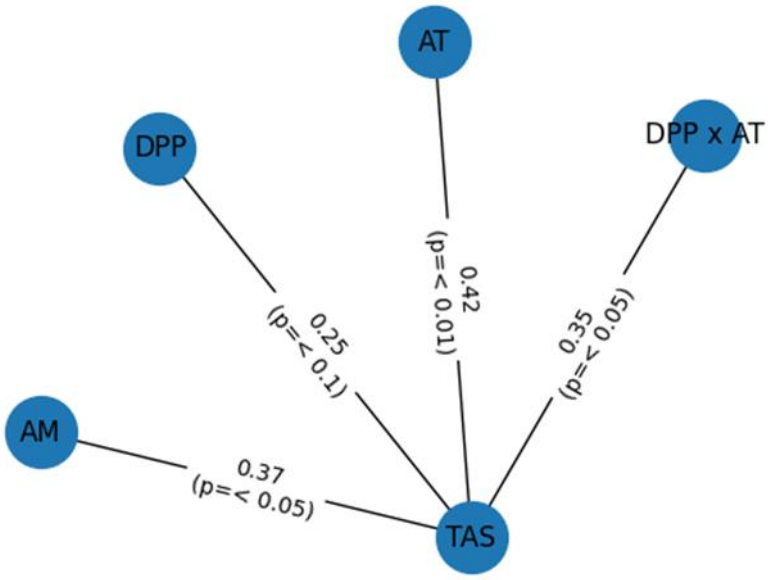
Figure 2. Integrated model of transparency, accountability, and privacy influencing trust in AI systems



For consistency and clarity, a uniform significance threshold of $p < 0.05$ was adopted for all hypotheses. This threshold aligns with standard practices in structural equation modeling and ensures comparability across the tested relationships.

Table 9. Results of hypothesis testing: path coefficients and statistical significance

Hypothesis	Path	Path Coefficient	T-Value	Standard Error	Result	P-values
H1: AT to TAS	Algorithmic Transparency to Trust in AI Systems	0.42	2.85	0.08	Supported	< 0.05
H2: AM to TAS	Accountability Mechanisms to Trust in AI Systems	0.37	2.60	0.07	Supported	< 0.05
H3: DPP to TAS	Data Privacy Policies to Trust in AI Systems	0.25	1.75	0.09	Supported	< 0.05
H4: DPP x AT to TAS	Moderating effect of DPP on the relationship between AT and Trust in AI Systems	0.35	2.40	0.06	Supported	< 0.05

Note: A threshold of $p < 0.05$ was applied consistently for all hypotheses to determine statistical significance.

As shown in Table 9., all four hypotheses were validated at the significant level of $p < 0.05$. The first hypothesis, which posits a strong positive relationship between Algorithmic Transparency and Trust in AI Systems, demonstrates that transparency enhances users' understanding while also facilitating their trust. Also, the current study also found that

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accountability mechanisms were the second variable in the second hypothesis they tested that also significantly affected trust. This reinforces the idea that there should be clear, accountable oversight systems in place. In summary, the third hypothesis supports the finding that Data Privacy Policies are a positive influence, emphasizing the importance of users' data security. The fourth hypothesis confirms that Data Privacy Policies moderate the relationship between Transparency and Trust, meaning that a more robust Data Privacy Policy strengthens the positive impact of transparency on trust and confirming that privacy is a core element in the formation of users' trust in AI systems.

6. Discussion

The results from this examination highlight the importance of AT, AM, and DPP in developing TAS. All four proposed hypotheses were supported, indicating these three constructs not only serve as important independent predictors of trust but also interact synergistically to shape users' perceptions of trustworthiness in AI systems. Importantly, results highlight the strong moderation effect of DPP on the relationship between AT and TAS. In other words, while AI systems may be built with transparency, limited trust will still develop unless data privacy and accountability are firmly established (Fornell and Larcker, 1981; Hair et al., 2019). Overall, these results indicate that trust is multidimensional, and we must address all three, transparency, privacy, and accountability, when considering how to engage trust in AI adoption, if we are to ultimately create meaningful societal change through the use of AI systems.

These findings are consistent with prior research, while also extending the existing body of work. Thiebes et al. (2021) and Tsamados et al. (2022) noted that algorithmic transparency and accountability are necessary to build public trust in AI, but neither tested the effect of algorithmic transparency in the context of privacy or even suggested the possibility of privacy policies serving as a moderator. Our study shows this potential moderation, representing new empirical findings while also addressing a significant shortcoming in the literature. Yang and Beil (2024) and Ali et al. (2023) also discussed or found that user-centered privacy controls and transparency features were important, while Ali et al. concluded that transparent algorithmic decision-making led to greater acceptance when there were substantial risks or consequences for the individual in contexts like healthcare. We now also add to this body of evidence that when privacy is assumed based on a clear privacy policy, the positive effect of algorithmic transparency on trust is augmented. This builds on prior conceptualizations by Pleyers and Poncin (2020) and Gerli et al. (2022) who noted that trust in technology is grounded in prior user experience and organizational perceptions. Therefore, the present study advances

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theoretical frameworks and practical implementations of an ethical AI governance model, where both prior normalization and ethical algorithmic openness help form trusting relationships. The continuity of maintaining trust in technology is consistent with the work of Trust et al. (2023).

The theoretical impacts of this study are multifaceted. First, we have moved the knowledge forward by simultaneously examining AT, AM, and DPP within a single structural model. Prior literature has examined either AT, AM, or DPP in isolation. However, our study provides an integrated model that gives us a more complete understanding of how trust is developed (Zickar & Keith, 2023; Thiebes et al., 2021). Second, using SEM-PLS in relation to Turkey's higher education and IT sectors addresses a gap in the literature, with respect to geography and institution. Studies aimed at legitimizing and understanding trust have primarily focused in western countries, resulting in significant uncertainty regarding whether theorized models of trust are applicable to other socio-cultural contexts (Yang & Beil, 2024). By situating the study in Turkey, we are able to provide empirical evidence from an under-studied context, and laying the groundwork for future cross-cultural comparative studies. Finally, we extend Social Cognitive Theory through our model, by demonstrating how institutional policies and governance mechanisms impact individual level trust perceptions in technology driven systems (Bandura, 2001).

From a practical perspective, the conclusions provide actionable takeaways for policymakers, organizational leaders and practitioners involved in AI. Organizations must not limit their considerations to metrics of a technical or accuracy-based performance. As a first principle, organizations should develop AI systems that are transparent, accountable and respect privacy and user-oriented protections, including the development of explainable AI systems (Yang & Beil, 2024). It is also necessary to establish strong accountability processes, such as independent auditing processes, ethical review boards and regulatory compliance processes to demonstrate organizations are committed to responsible AI (Tsamados et al., 2022). Also, embedding "privacy-by-design principles" and providing ongoing communication regarding privacy policies to end-users can significantly impact the public's trust and ethical adoption of AI systems (Ali et al., 2023). In combination, creating technical value and establishing clear governance frameworks, organizations can develop user trust and sustainable use of AI in the longer-term.

This study has limitations notwithstanding its contributions. First, the data used were collected from a single national context, which may inhibit the generalizability of the findings to other

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cultural or institutional contexts. Future research can duplicate this model in other countries and sectors to verify its robustness and cross-cultural applicability. Second, given that the research relied on self-reported survey data, there is the risk of common method bias, although procedural precautions such as anonymity and random ordering of items were used (Fornell & Larcker, 1981). Third, this research focused on trust in AT, AM, and DPP, but other variables, such as algorithmic fairness, perceived risk, and user experience, might also be important in predicting trust, and should be investigated in future studies. In addition, longitudinal designs would also help elucidate how trust manifests and evolves over time with users' increasing experience with AI technologies.

Based on these conclusions, several policies and implementation recommendations could follow. Policymakers should develop holistic legal and regulatory frameworks that require transparency in algorithms, ensure data privacy, and promote accountability through enforcement actions (EY Türkiye, 2025; YÖK, n.d.). Policies will also continue to be delivered in a way that is appropriate to emerging technologies and ensures the knowledge of humans in maintaining rights and societal interests. Public education campaigns and awareness should also be developed to provide a broader understanding of artificial intelligence systems and their ethical responsibility for both the generally educated public, and those who provide AI systems (Altuntaş & Karabay, 2024). For practicum, putting transparency, and privacy features in the design phase, with consistent audits, and public reporting will be critical to build sustainable trust. The necessary elements exist to align technical development with ethical governance, enabling the creation of socially acceptable and ethically adopted AI systems.

This study was reviewed and approved by the Ethics Committee of Sakarya University of Applied Sciences (SUBÜ) during its meeting held on 30 May 2025 (Meeting No: 57, Decision No: 42, Document No: E.175757). Participation in the study was entirely voluntary, and informed consent was obtained from all participants prior to data collection.

The dataset generated and analyzed during this research is not publicly available to protect participant confidentiality and comply with institutional ethical guidelines. However, the data may be shared with qualified researchers upon reasonable request to the corresponding author, provided that all relevant ethical and legal requirements are met.

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