



# BUILDING MUTUAL TRUST IN PEER-TO-PEER RESALE MARKETPLACES

An Entrepreneurial Examination of Trust Mechanisms in  
the Saudi Recommerce Ecosystem

## ABSTRACT

Trust functions as the critical currency of peer-to-peer resale marketplaces, particularly in emerging digital economies such as Saudi Arabia. This research examines how platform-level trust mechanisms—including identity verification, reputation systems, protected payments, and dispute resolution—shape user confidence and influence transaction-related outcomes in the Saudi recommerce ecosystem. The study conceptualizes trust not merely as a behavioral concern but as an entrepreneurial design lever that directly affects platform

viability, scalability, and network effects.

Drawing on institution-based trust theory, signaling theory, and the Technology Acceptance Model (TAM), the research proposes a refined conceptual model distinguishing between trust in peer counterparties and trust in the platform's governance and infrastructure. A quantitative, survey-based methodology is employed to examine how trust mechanisms influence perceived safety, perceived usefulness, and transaction-related intentions. The findings aim to generate actionable insights for platform entrepreneurs, investors, and

policymakers seeking to design trust-centric resale platforms aligned with Saudi Arabia's Vision 2030 and circular economy objectives.

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# 1. Overview of the Study

## 1.1 Introduction

The digital peer-to-peer resale market in Saudi Arabia has grown rapidly in recent years, driven by increased smartphone usage, shifting consumer behavior, and the national push toward digital transformation under Vision 2030. Yet despite this growth, **trust remains a critical barrier** preventing smooth and successful peer-to-peer transactions. This research topic was chosen because of a persistent gap between consumer demand for secondhand goods and the lack of structured trust systems within existing platforms. Historically, resale in Saudi Arabia relied on personal relationships and informal verification; the shift to online peer-to-peer exchanges has introduced new uncertainties that require modern institutional and technological solutions. **This proposal therefore examines trust-building mechanisms not merely as user-experience enhancements but as fundamental enablers of viable, scalable recommerce business models.** It explores the roots of the trust challenge and identifies mechanisms to enhance credibility, safety, and confidence in digital resale environments from an **entrepreneurial perspective**.

## 1.2 Background of the Study

The rapid expansion of peer-to-peer resale marketplaces has created a new wave of entrepreneurial opportunities in the digital recommerce sector. Platforms such as Haraj.sa, Soum.sa, and OpenSooq enable individuals to exchange used goods directly, forming a vibrant secondary market that aligns with global sustainability trends and the circular economy. In Saudi Arabia, this digital shift is accelerated by high internet penetration, widespread mobile commerce, and a national emphasis on innovation and digital entrepreneurship under Vision 2030.

While the recommerce sector is growing in economic relevance, building a sustainable venture in this domain remains challenging. **Unlike traditional B2C e-commerce, peer-to-peer resale involves interactions between strangers with minimal platform-enforced**

**safeguards, informally structured negotiations, and a high degree of information asymmetry.** For entrepreneurs seeking to build scalable recommerce startups, **trust formation is not merely a user-experience issue, it is a fundamental business viability challenge.** Industry projections indicate that the Saudi recommerce market will reach USD 1.75 billion in 2025 and USD 2.88 billion by 2029, revealing substantial entrepreneurial potential. Yet this potential cannot be fully unlocked without addressing the trust barriers that inhibit transaction completion, repeat usage, and platform loyalty. From an entrepreneurial perspective, understanding trust mechanisms is a prerequisite for designing scalable platform models, reducing friction, and enabling market growth. In short, this study reframes trust not only as a behavioral phenomenon but as a **core entrepreneurial design factor** that directly influences customer acquisition, platform adoption, and long-term venture sustainability.

### 1.3 Problem Statement

Although Saudi Arabia hosts one of the region's most active peer-to-peer resale markets, entrepreneurs in the recommerce sector face a major barrier to building scalable and profitable ventures: the absence of structured **trust mechanisms** that ensure safe, credible, and reliable transactions. Current resale platforms rely heavily on informal negotiation, unverified identity cues, and user-generated descriptions, leading to:

- **Buyer concerns** about misrepresentation or fraud (e.g. product condition not as described).
- **Seller concerns** about non-serious buyers, excessive bargaining, or buyers backing out after an agreement.
- **Inconsistent user-experiences** that undermine repeat usage and word-of-mouth growth.

From a venture creation standpoint, these trust problems translate into:

- Low conversion rates (many initiated deals never close).
- High abandonment rates and transaction drop-offs.

- Limited user retention and engagement.
- Difficulty in scaling network effects (users hesitate to transact with unknown parties).
- Weak differentiation from competitors (trust issues plague all similar platforms).
- An inability to establish a defensible, sustainable business model.

Despite the commercial scale of recommerce activity, there is a lack of research examining trust as an **entrepreneurial constraint** and identifying which platform-level mechanisms can support the growth, sustainability, and competitiveness of emerging recommerce ventures. This study seeks to close that gap by evaluating trust-building mechanisms through an explicitly entrepreneurial lens.

## 1.4 Entrepreneurial Opportunity

The growth trajectory of Saudi Arabia's digital economy presents a significant entrepreneurial opportunity in the recommerce sector. Several factors create favorable conditions for venture creation:

1. **Market Size & Growth Potential:** The recommerce market's projected multi-billion-dollar value signals robust demand and increasing consumer acceptance of buying used goods. This unmet demand represents fertile ground for innovative marketplace startups that can establish trust and draw in hesitant users.
2. **Market Inefficiencies as Startup Opportunities:** Existing platforms lack structured trust infrastructure and leave large "pain points" unaddressed. These inefficiencies are strategic entry points for founders to create value through implementing features such as verified user identities, protected payments (escrow services), standardized product condition reporting, AI-assisted authenticity checks, and efficient dispute-resolution systems. Each mechanism functions as a distinct value proposition, allowing a startup to differentiate itself and gain competitive advantage by solving trust pain points that incumbents have overlooked.
3. **Network Effects & Scalability:** Trust is a gateway to achieving network effects. When users feel safe and confident, they transact more frequently, list more items, and invite others to join—amplifying organic growth and lowering customer acquisition

cost (CAC). Effective trust mechanisms are therefore essential for reaching the critical mass needed for a scalable, venture-backed platform. In essence, **engineered trust enables liquidity**, which feeds back into stronger network effects.

4. **Alignment with Vision 2030:** Saudi Arabia's national digital transformation agenda and Vision 2030 initiatives support recommerce startups through regulatory encouragement (e.g. e-commerce laws that recognize digital transactions), entrepreneurship development programs, and a growing tech innovation ecosystem. This favorable environment means that a trust-focused recommerce venture aligns with national priorities, potentially easing access to support and investment. In summary, the recommerce sector offers high potential for new ventures—but capturing this opportunity requires platforms to strategically engineer trust as part of their core business model.

## 1.5 Research Questions

Main Research Question:

How can trust-building mechanisms strengthen mutual buyer–seller confidence and enable the viability and scalability of recommerce startups in Saudi Arabia?

Sub-questions:

1. What factors drive buyer distrust in peer-to-peer resale transactions?
2. What factors drive seller distrust in these transactions?
3. Which platform trust mechanisms do users perceive as most effective for building confidence (e.g., identity verification, ratings, secure payment)?
4. How do these trust mechanisms influence users' willingness to complete transactions?
5. How can insights about trust be applied to the design and strategy of entrepreneurial recommerce platforms?

## 1.6 Research Objectives

Primary Objective:

To evaluate which trust-building mechanisms enhance user confidence and support the business viability, scalability, and competitive advantage of recommerce startups in Saudi Arabia.

Secondary Objectives:

- Identify the key drivers of buyer-side distrust and seller-side distrust in peer-to-peer resale.
- Measure user perceptions of specific trust mechanisms (such as identity verification, reputation systems, protected payments, AI-assisted checks, and standardized product information).
- Examine how implementing trust mechanisms influences users' intention to complete transactions and their likelihood of repeatedly using the platform.
- Translate the findings into **entrepreneurial design principles** for marketplace startups, offering guidance on which trust features to prioritize to improve platform performance.

## 1.7 Significance of the Study

This study contributes to the field of entrepreneurship by reframing digital trust as a **core strategic resource** for recommerce platform ventures. By empirically identifying how trust mechanisms affect user behavior, the findings will help platform founders and designers:

- **Design trust-centric business models:** Incorporate trust features into the venture's value proposition from the outset.
- **Reduce transaction friction:** Lower the barriers that cause drop-offs, thereby increasing successful exchanges.
- **Increase conversion and retention:** Improve the rate at which browsing leads to completed sales and encourage users to return for future transactions.

- **Differentiate from competitors:** Provide a safer, more reliable user experience that sets the venture apart in the marketplace.
- **Build scalable, investment-ready ventures:** Strengthen network effects and user loyalty, making the platform more attractive for growth and external investment.

Policymakers, incubators, and support programs may also benefit from these insights by focusing on trust infrastructure when developing the digital entrepreneurship ecosystem. In sum, by treating trust as an entrepreneurial enabler rather than a mere afterthought, the study's outcomes can guide more sustainable and competitive platform development in Saudi Arabia's digital economy.

## 1.8 Scope of the Study

The study will focus on individuals in Saudi Arabia who have experience buying or selling used goods on online peer-to-peer platforms. The research emphasizes broad **entrepreneurial implications** for building trust in recommerce ventures, rather than evaluating any single existing platform's business model or endorsing specific companies. The analysis is kept general enough to apply to the Saudi recommerce ecosystem as a whole. The scope is limited to **perceptions and intentions** in the current market environment (as captured through a survey), recognizing that actual behavior might differ and that findings are context-specific to Saudi Arabia and possibly the GCC region.

## 1.9 Definition of Terms

- **Resale Marketplace:** A digital platform that facilitates peer-to-peer exchange of used goods (also known as recommerce or consumer-to-consumer e-commerce). Examples include online classifieds and dedicated resale apps where individuals buy and sell secondhand items.
- **Mutual Distrust:** A situation in which both buyers and sellers in a transaction perceive risk and uncertainty about the other party's honesty or reliability. Mutual distrust can manifest as buyers fearing fraud and sellers fearing non-payment or opportunistic behavior.

- **Trust Mechanisms:** Platform features or policies designed to reduce ambiguity and increase reliability in transactions. In this study, trust mechanisms refer to features like identity verification, user rating/reputation systems, protected payment systems (escrow), standardized product condition reporting, transparent pricing guidance, and clear dispute resolution processes. These mechanisms aim to foster greater confidence between transacting parties by providing assurances or information that would otherwise be absent in a peer-to-peer exchange.

## 2. Literature Review

### 2.1 Trust in Peer-to-Peer Digital Exchanges

In peer-to-peer resale markets, transactions hinge on interpersonal trust because there are few formal guarantees to ensure honesty, product quality, or commitment to completing the exchange. Buyers must trust that sellers accurately describe the item and will deliver it as promised, while sellers must trust that buyers are genuine and will follow through with payment. Unlike a traditional retail scenario, a platform often acts only as a facilitator and does not fully vouch for transactions, making trust between users paramount. Prior research on online marketplaces highlights that when trust is low, users engage in protective behaviors (e.g. excessive bargaining, demanding cash on delivery) or avoid transactions altogether. Thus, establishing trust is essential to reduce uncertainty and enable smoother transactions in peer-to-peer settings.

### 2.2 Mutual Distrust as a Transaction Barrier

Mutual distrust arises when both parties in a potential deal suspect the other might behave opportunistically. This double-sided skepticism creates a significant transaction barrier: it slows down negotiations, increases the effort required to verify information, and leads to a higher incidence of abandoned transactions. For example, a buyer who doubts a seller's honesty might delay payment or request unnecessary proof, while a seller who doubts a buyer's seriousness might decline offers or avoid listing high-value items. **Mutual distrust**

**reduces market efficiency** – fewer deals are closed and those that do close may take longer and involve more stress. In the context of Saudi peer-to-peer commerce, these issues are exacerbated by a historical reliance on face-to-face trust cues; transitioning to online interactions without established digital trust frameworks leaves a void that can stall the growth of the marketplace.

## 2.3 Global Studies on Digital Resale Marketplaces

Global research on major resale platforms (such as eBay, Facebook Marketplace, and Craigslist) demonstrates that various features can mitigate uncertainty and foster trust. Key findings from the literature include:

- **Identity Verification:** Verifying user identities (through ID checks, verified badges, etc.) reduces anonymity-based risks and holds users accountable, thereby increasing trust.
- **Reputation and Rating Systems:** Allowing buyers and sellers to rate each other and display feedback provides a **signal of past reliability**. High ratings or positive reviews serve as social proof that increases others' confidence in transacting.
- **Protected Payment Services:** Secure payment mechanisms (such as escrow, buyer protection, or platform-held payments) increase the buyer's sense of safety that they will not lose money to a fraudulent seller. Sellers also benefit when buyers have confidence to pay online.
- **Standardized Product Descriptions:** Using templates or guidelines for condition reporting (and even incorporating verification of item conditions) reduces ambiguity about product state. Less uncertainty about what is being sold means fewer surprises and disputes, thus building trust.
- **Transparency Tools:** Some platforms introduce pricing guidance or authenticity checks (increasingly with AI tools) to assure users that the deal is fair and the item is as advertised. These tools can enhance perceptions of **fairness** in the transaction.

Overall, these studies suggest that the design of **platform trust-building mechanisms** plays a crucial role in supporting user confidence. However, they also note that such

features must be adapted to the cultural and market context – what works in one country or platform may not directly transfer to another without considering user norms and expectations.

## 2.4 The Saudi Resale Marketplace Environment

In Saudi Arabia's resale platforms, formal trust infrastructure is still emerging. For example:

- **Haraj.sa** – the leading local classifieds platform – follows an open marketplace model with minimal structured safeguards. Transactions are often negotiated via chat, and the platform provides limited intervention, which puts the onus of trust entirely on users' personal judgments.
- **Informal Social Markets** – Many Saudis also use social media (Instagram, Snapchat) or community WhatsApp groups to sell items. These rely heavily on personal networks, word-of-mouth reputation, and informal trust cues (like knowing a friend-of-a-friend), rather than platform-provided assurances.
- **Soum.sa** – a newer platform – has introduced some verification and structured listing rules (for instance, verifying phone numbers or offering standardized pricing suggestions). Early indications suggest that introducing such **institutional mechanisms** can reduce distrust and support marketplace growth by making users feel more secure.

Overall, Saudi peer-to-peer resale is at a developmental stage where **platform-managed trust systems are not yet fully mature**. This presents an opportunity for research and innovation: by studying which trust mechanisms would resonate in the local context, entrepreneurs can design better platforms. It also means that lessons from global platforms need to be interpreted through a local lens – for instance, understanding the **cultural importance of interpersonal trust and community reputation** in Saudi Arabia, and how that can be augmented with formal mechanisms.

## 2.5 Trust Mechanisms as Enablers of Transaction Confidence

Trust mechanisms are the features or policies intentionally designed to reduce uncertainty in peer-to-peer exchanges. Key examples relevant to this study include:

- **Identity Verification:** Requiring users to confirm their identity (e.g. government ID, mobile number verification, or unified national digital IDs) to increase accountability. Verified profiles give both buyers and sellers greater confidence that the other party is genuine.
- **Reputation Systems:** User reviews, star ratings, or badges (such as “Top Seller”) signal a user’s history and reliability. A strong reputation can reassure counterparties of a user’s trustworthiness.
- **Protected Payments:** Services like escrow accounts, cash-on-delivery with verification, or payment guarantees ensure that money and goods exchange hands under agreed conditions. This protection reduces the perceived risk of fraud or non-payment in online deals.
- **Standardized Condition Reporting:** Enforcing or encouraging detailed listings with condition categories, photos, or even third-party inspection for high-value items. This lowers information asymmetry by making sure buyers know what they are getting and sellers disclose key details, thereby increasing the **perception of fairness** in the transaction.
- **Transparent (or AI-Assisted) Pricing:** Providing price benchmarks or suggested price ranges for used items using data or AI can make pricing negotiations feel more fair and grounded. When pricing is seen as fair, trust between buyer and seller improves because neither side feels significantly disadvantaged.
- **Clear Dispute Resolution Procedures:** Having a structured process (and possibly platform mediation) for handling complaints or returns can assure users that if something goes wrong, there is a fair remedy. Knowing that disputes can be resolved reduces the fear of worst-case outcomes.

Each of these mechanisms is intended to **foster mutual confidence** by addressing specific causes of distrust (identity uncertainty, quality uncertainty, payment risk, etc.). By implementing a combination of these tools, a platform can create an environment of structural assurance where users feel the system itself helps safeguard their interests.

## 2.6 Conceptual Model

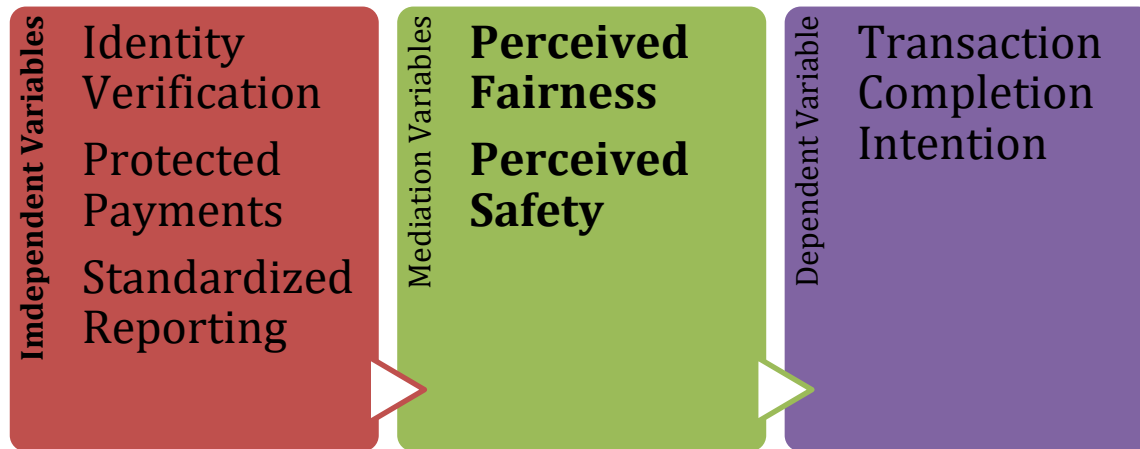
Building on the above insights, this study proposes an enhanced conceptual model that distinguishes between two levels of trust – **trust in the platform** and **trust in one's peer (counterparty)**. The model posits that implementing robust trust mechanisms (independent variables) directly strengthens users' trust in the platform's systems (confidence that the **platform** is safe and reliable) as well as trust in other users (confidence that the **peer** is honest and dependable). In turn, these improved trust perceptions are expected to increase users' intention to complete transactions (the dependent variable). In other words, platform features like secure payment escrow and dispute resolution provide structural assurances that bolster trust **in the platform**, while features like verified profiles and rating systems signal user credibility and bolster trust **in peers**. When users feel confident both in the platform **and** in the person they are dealing with, they should be far more likely to follow through with a sale or purchase. *(Notably, this framework also accounts for technology adoption factors: if a trust mechanism is not user-friendly or its benefit is unclear, users may not utilize it (Davis, 1989), limiting its effectiveness. Thus, consistent with TAM principles, the model assumes trust features must be perceived as useful and easy to use to fully yield their intended effect.)*

For example, **Identity Verification** provides a dual benefit: it increases institutional assurance (users know the platform has verified identities – enhancing trust in the platform) and it increases interpersonal credibility (verified badges make buyers and sellers more accountable – enhancing trust in the peer). Likewise, a **secure payments** feature primarily boosts trust in the platform by ensuring safer transactions, whereas a **user rating system** primarily boosts trust in peers by revealing others' reliability through feedback. In practice,

these mechanisms work in combination – a platform that, say, verifies users’ identities and offers an escrow payment option is simultaneously signaling that “the system will protect you” and “this person has been vetted,” addressing both trust dimensions.

Based on this model, the primary expectation is that trust mechanisms will **indirectly** drive transaction completion by first elevating platform trust and peer trust as mediators. However, the design does not rely on a single mediation path; it acknowledges that trust features might also exert some **direct** influence on transaction behavior. Simply knowing that a platform has strong safeguards can reassure users and nudge them toward completing a deal, even if they don’t consciously dwell on specific fairness or safety perceptions. The following hypotheses summarize the key relationships:

- **H1:** The implementation of platform trust mechanisms (e.g., identity verification, ratings, secure payments) is positively associated with users’ **perceived fairness** of transactions. (Users will feel the exchange is fairer when trust features are in place.)
- **H2:** The implementation of platform trust mechanisms is positively associated with users’ **perceived safety** in transactions. (Users will feel more secure and protected on the platform with these features.)
- **H3:** Users’ **perceived fairness** in the platform’s transactions is positively related to their **intention to complete** transactions. (When users feel a deal is fair to both parties, they are more likely to go through with it.)
- **H4:** Users’ **perceived safety** in transactions is positively related to their **transaction completion intention**. (When users feel safe from fraud or loss, they are more inclined to finalize transactions.)
- **H5:** Perceived fairness and perceived safety **mediate** the relationship between trust mechanisms and transaction completion intention. In other words, platform trust mechanisms will lead to higher completion intentions **because** they first increase fairness and safety perceptions. (This hypothesis reflects the indirect pathway central to the conceptual model.)



**Figure 1. Conceptual Model of Trust in Saudi Resale Platforms**

This model illustrates how platform trust mechanisms are hypothesized to increase users' trust in the platform and in other users, ultimately influencing their willingness to complete transactions. These hypotheses will be examined with survey data as outlined in the methodology. Supporting evidence for them would underscore that entrepreneurs need to engineer both institutional and interpersonal trust factors to overcome transaction barriers in peer-to-peer resale marketplaces.

## **2.7 Theoretical Framework Linkage**

To ground this study, we draw on established theories that correspond to each **trust dimension** – institutional trust (trust in the platform) and interpersonal trust (trust in peers) – and we incorporate insights from technology adoption theory to complete the framework. In particular:

- **Institution-Based Trust and Structural Assurance:** This perspective (pertaining to trust in the platform as an institution) suggests that formal structures, rules, and institutions can create a baseline of trust in a market. Zucker (1986) introduced the

idea that trust can be “produced” through institutional mechanisms, meaning people trust a system when there are safeguards and commitments embedded in it. In our context, features like verified identities, standardized dispute processes, and protected payment systems provide structural assurance – they signal that the platform itself is committed to fairness and accountability. When users perceive the platform as enforcing clear rules and protections, their confidence in dealing with strangers increases. This aligns with commitment-trust theory in relationship marketing, where an organization’s demonstrated commitment to safe, reliable transactions fosters trust among participants (Morgan & Hunt, 1994). In short, strong institutional mechanisms reduce uncertainty and build users’ **trust in the platform** environment.

- **Signaling Theory:** Signaling theory addresses trust at the interpersonal level. It explains how one party can communicate credible information to another under conditions of uncertainty (Spence, 1973). In online resale markets where buyers and sellers lack prior relationships, visible trust cues act as signals of credibility between users. For example, a verified seller badge, a high star-rating, or an authenticated product photo are signals that convey information about a user’s quality or integrity (Connelly et al., 2011). Effective signals are hard to fake and easy to observe – thus, they bridge the information gap. By applying signaling theory, each trust mechanism is viewed as a **signal**: a way for the platform or its users to communicate “you can trust this transaction.” When these signals are present and credible, they alleviate fears and lead to greater **trust in the counterpart**. In essence, robust signaling features build users’ trust in their peers on the platform by making reputations and reliability more transparent.
- **Technology Acceptance Model (TAM):** In addition to trust-specific theories, TAM provides a complementary lens focusing on user adoption of the platform’s features. TAM posits that a user’s intention to use a technology is driven largely by

perceived usefulness and perceived ease of use (Davis, 1989). In our context, even the best trust feature only matters if users actually use it; thus, if a trust-building feature (e.g. an escrow payment system or an ID verification step) is perceived as easy to use and clearly useful for making transactions safer, users are more likely to embrace it and complete transactions. Conversely, if a trust mechanism is cumbersome or its benefit unclear, users might bypass it entirely, limiting its effectiveness. By integrating TAM, our framework acknowledges that the impact of trust mechanisms on completion intention also depends on the user experience and acceptance of those mechanisms. In other words, the success of these trust features requires that users find them accessible and beneficial – a reminder that **user adoption** is critical to translating trust mechanisms into actual marketplace behavior.

Ultimately, this integrated theoretical foundation addresses both **dimensions of trust** – the institutional trust in the platform’s safeguards and the interpersonal trust between users – while also considering the importance of user acceptance. It guided our survey design (with measures for perceived platform safety, peer credibility, and feature usefulness) and it will inform the interpretation of results. By combining these perspectives, we take a holistic view of how trust can be cultivated and translated into user engagement on peer-to-peer resale platforms.

## **2.8 Regional and Cultural Context (Saudi/GCC Studies)**

In the context of digital commerce in Saudi Arabia, both structural conditions and cultural norms shape the need for effective trust mechanisms. Saudi Arabia’s internet penetration is near-universal (~99%), and the nation is essentially a mobile-first society with more active mobile subscriptions than people (over 115% mobile penetration). This connectivity has fueled rapid growth in overall e-commerce. However, the dedicated peer-to-peer recommerce sector remains emergent and relatively under-studied in academic literature, meaning platforms often operate on assumptions without local data on trust dynamics.

Regional studies that do exist highlight how trust online is heavily influenced by social and cultural factors. Users in Saudi Arabia and neighboring GCC countries tend to rely more on community reputation and personal assurances than on impersonal system guarantees when transacting in informal online markets. For instance, a recent Saudi social commerce study by Aldera et al. (2025) found that consumers' trust in informal Instagram resale was driven primarily by the **seller's reputation** and perceived transaction safety, whereas platform-provided information quality had negligible effect on purchase intention. In other words, who you are dealing with (and how safe the interaction feels) often matters more to local users than generic platform assurances. Similarly, Curtis et al. (2020) note that certain platform design features – like rigorous identity verification and active community moderation – can significantly bolster users' sense of safety in sharing-economy marketplaces. This suggests that building trust in the Saudi/GCC context requires addressing the interpersonal level (ensuring the **trustworthiness of other users**) in addition to adding formal protections.

Cultural expectations around trust also play a key role. An industry report (Zigpoll, n.d.) emphasizes that transparent and timely dispute resolution is critical in the Gulf region: slow or opaque handling of problems can quickly erode user confidence, as personal honor and fairness are highly valued. Users expect that if an issue arises, it will be resolved in a manner they perceive as just; unclear or drawn-out processes violate this expectation and thus undermine trust. Together, these insights suggest that any trust-building mechanisms must be attuned to local norms and behaviors. It may not be sufficient to simply import features from Western platforms—success in Saudi's P2P markets will likely come from blending global best practices with local customs. For example, platforms might incorporate trust signals that resonate with Saudi users' preferences (prominent verification badges, endorsements from known community figures, integration with popular social networks for identity) and ensure support processes align with cultural notions of fairness and respect. This study extends the regional literature by empirically testing how specific trust cues (e.g. verified identity badges, transparent pricing guidance, clear dispute policies) correlate with users' intentions to complete transactions in the Saudi setting. In doing so, it contributes a

localized model of trust for peer-to-peer commerce in the GCC context, shedding light on how cultural factors mediate the effectiveness of various trust mechanisms.

### 3. Research Methodology

#### 3.1 Research Design

This research will employ a quantitative cross-sectional survey design to test the relationships outlined in the conceptual model. The primary data will be collected through a structured online questionnaire capturing: (a) buyer-side and seller-side distrust factors, (b) perceived effectiveness of various trust mechanisms, (c) overall trust perceptions of the platform environment (e.g. fairness, safety), and (d) intentions to complete transactions. This design allows for statistical analysis of correlations and exploratory causal inferences (through regression) at a single point in time. **Importantly, the study is not a comparative analysis of any two specific platforms (e.g. Haraj.sa vs. Soum.sa); instead, it takes a platform-agnostic approach, surveying users across the Saudi recommerce space to focus on general trust dynamics rather than platform-by-platform differences.** The choice of a survey is appropriate given the focus on individual perceptions and the need for quantifiable measures of constructs like trust. The survey method also aligns with course guidance by yielding SPSS-ready data and a reproducible analysis process. Given the high level of internet connectivity in Saudi Arabia (and active online communities for resale on social media and forums), an online questionnaire is both feasible and efficient for reaching the target sample. *(While the primary approach is quantitative, the study remains open to incorporating a few qualitative insights—e.g. an open-ended comment or brief follow-up interviews for context—though these would be strictly supplementary.)*

#### 3.2 Population and Sampling

- **Target Population:** Individuals in Saudi Arabia who have experience in buying or selling used goods online (via any peer-to-peer platform or social media). This

includes both frequent and occasional users of recommerce platforms, as both perspectives on trust are valuable.

- **Sampling Method:** A purposive convenience sampling strategy will be used. Participants will be recruited through online channels such as resale platform user groups, community marketplace forums, and social media communities (Twitter, Facebook groups) where recommerce is discussed. This approach targets respondents who are likely familiar with the context of interest. To improve representativeness, the sample will aim for diversity across key demographics (gender, age groups, and region within Saudi Arabia) and user roles (ensuring we include both those who primarily buy and those who primarily sell secondhand goods).
- **Sample Size:** The goal is to collect responses from approximately 60–120 participants, with ~100 being ideal. A sample of 100 respondents can provide a reasonable balance between feasibility and statistical insight for an exploratory analysis. While not statistically random, a sample of this size can yield roughly 90% confidence level with a 10% margin of error for descriptive findings, which is acceptable in an exploratory study of an emerging market context. The emphasis is on detecting clear relationships (if present) rather than achieving nationwide generalizability. All participants will be assured anonymity and that the data will be used for academic purposes only.

### 3.3 Data Collection Instrument

Data were collected using a structured online questionnaire implemented via Google Forms. The survey was designed as a self-administered form and was made available in both English and Arabic to maximize clarity and reach. At the start, respondents saw a brief introduction explaining the study's purpose (to examine trust issues and mechanisms in peer-to-peer resale platforms) and a screening question confirming experience with buying or selling secondhand items online. Only those who answered "Yes" to having prior resale experience proceeded to the main questionnaire. Basic demographic questions followed,

capturing age group, gender, and region of residence, as well as the respondent's primary role on resale platforms (e.g. mostly buyer, mostly seller, or both). These questions established the context of the sample (for instance, the final sample of N = 164 valid respondents was fairly balanced in demographics and roles, ensuring relevance to the Saudi recommerce context).

The main part of the questionnaire consisted of multiple Likert-scale statements organized by construct. Each statement was closed-ended and answered on a five-point agreement scale ranging from "Strongly Disagree" (1) to "Strongly Agree" (5). The survey instrument was structured into sections corresponding to key constructs derived from the conceptual model: buyer distrust, seller distrust, trust-building mechanism perceptions, perceived fairness, perceived safety, and transaction completion intention. The items under each construct were formulated based on the study's hypotheses and literature review, ensuring that they directly tap into the concepts of interest (e.g. distrust factors, trust features, etc.). The wording was kept clear and concise in line with best practices (avoiding double-barreled or leading questions), and important terms were provided in Arabic alongside English for bilingual clarity. Prior to launching the survey, the instrument's content was reviewed by an academic advisor for content validity – this helped confirm that each question was relevant to its intended construct and easily understood by the target audience. Minor adjustments in phrasing were made based on this feedback. The finalized Google Form thus provided a reliable vehicle for data collection, with its structure mirroring the conceptual framework of the research. All responses were automatically recorded in a spreadsheet via Google Forms, facilitating a smooth transition to data analysis.

### **3.4 Survey Statements**

Each construct in the survey was measured by multiple Likert statements (with 1 = *Strongly Disagree* and 5 = *Strongly Agree*). Below is an overview of the survey statements grouped by their corresponding construct (the full bilingual questionnaire is provided in **Appendix A**):

- **Buyer Distrust** – These items gauge concerns that a buyer might have when considering a purchase on a peer-to-peer resale platform (higher agreement indicates greater buyer-side distrust):
  - *“Sellers may exaggerate the condition of the item.”*
  - *“Items might contain undisclosed defects.”*
  - *“Pricing in resale markets is sometimes perceived as unfair.”*
  - *“A lack of clarity in product descriptions reduces my willingness to purchase.”*
- **Seller Distrust** – These items capture concerns that a seller might have about engaging in a transaction (higher agreement indicates greater seller-side distrust):
  - *“Some buyers fail to complete transactions after negotiations, wasting the seller’s time.”*
  - *“Excessive bargaining is common in resale interactions.”*
  - *“Non-serious buyers often waste a significant amount of time for sellers.”*
  - *“I sometimes hesitate to list items because I am uncertain about buyer reliability.”*
- **Trust-Building Mechanisms** – These statements assess the perceived effectiveness or importance of various platform features designed to build trust (each feature identified from the literature as a potential trust mechanism):
  - *“Identity verification (e.g. verified user profiles or ID checks) increases the credibility of users on the platform.”*
  - *“Rating and review systems help me assess the trustworthiness of other users.”*
  - *“Protected payment methods (e.g. escrow services) would reduce transaction risks.”*
  - *“Standardized product condition reports can improve transparency about an item’s state.”*

- *“Transparent pricing tools (such as price guidelines) improve the perception of fairness in deals.”*
- *“Clear dispute resolution procedures increase my trust in the platform.”*
- **Perceived Fairness & Safety** – These items capture the overall trust environment perceptions on the platform:
  - *“I believe that transactions on resale platforms can be fair to both buyers and sellers.”* (Perceived Fairness)
  - *“I feel safe and secure when conducting transactions on these resale platforms.”* (Perceived Safety)
- **Transaction Completion Intention** – These statements measure the respondent’s willingness or intention to engage in transactions on the platform, particularly as influenced by trust considerations:
  - *“I would be more likely to complete transactions if the platform’s trust mechanisms were strengthened.”*
  - *“I would use resale platforms more frequently if I felt confident in the transaction process.”*
  - *“The presence of effective trust mechanisms influences my decision to complete a transaction rather than abandon it.”*

Each set of items above was intended to be aggregated into a scale representing its construct (e.g. the four buyer-distrust items collectively reflect an overall **Buyer Distrust** level for each respondent). By structuring the survey in this manner, the data allows for both item-level analysis and construct-level analysis. The inclusion of multiple items per construct (except for the single-item fairness and safety measures) helps improve measurement reliability, as discussed next. The full list of survey questions, including the bilingual presentation and answer options, is available in Appendix A for reference.

### 3.5 Validity and Reliability

**Content validity** of the instrument was established through careful design and expert review. As noted, academic advisors and experienced practitioners reviewed the draft survey to ensure that the items appropriately covered the domain of each construct. For example, they verified that the buyer distrust statements indeed encompassed common buyer concerns (product misrepresentation, pricing, etc.), and that the trust mechanism items reflected the key features identified in the literature. This review process led to high face validity of the instrument. Additionally, a small pilot test of the Google Form was conducted with a handful of representative users. Pilot respondents reported that the questions were clear and relevant, leading to only minor refinements.

After data collection, **internal consistency reliability** was assessed for each multi-item construct using **Cronbach's alpha**, calculated in Python. Table 3.1 below summarizes the reliability results for the main scales:

- *Distrust overall* (8 items combining both buyer and seller distrust facets) –  $\alpha = 0.635$ . This is slightly below the conventional 0.70 threshold, suggesting moderate consistency. It indicates that while the various distrust-related items are related, there is some diversity in the concerns (which is reasonable, given the scale spans multiple aspects of distrust). Notably, no single item's removal would dramatically raise the alpha, so all eight distrust items were retained to capture the full breadth of the construct.
- *Trust mechanisms* (5 items covering identity verification, ratings/reviews, condition reporting, pricing transparency, and dispute resolution) –  $\alpha = 0.505$ . This relatively low alpha suggests that respondents' views on different trust features were not highly correlated with each other. In other words, perceiving one mechanism as effective did not always imply the same for another. One reason is that these features are conceptually distinct (e.g. a user might strongly endorse ratings and dispute resolution, but be neutral about pricing tools). Given the exploratory nature of the study, we retained all these items and also examine them individually in the analysis;

however, the low reliability of this composite is acknowledged as a limitation. (*Note: The survey included a question on protected payments as well, which nearly all respondents strongly agreed with; this item was not included in the aggregated “trust mechanism” scale during analysis due to a lack of variance and to maintain consistency with the hypothesized feature set.*)

- *Transaction Intention* (3 items) –  $\alpha = 0.109$ . This very low alpha indicates that the three intention-related items did not behave as a unidimensional scale. Participants’ agreement with these statements varied widely item by item. For instance, some respondents agreed they’d use the platform more if confident (high on that item) but did not strongly link their behavior to specific trust mechanisms, or vice versa. Given this result, we treated the **Intention** construct cautiously. For analysis, an overall intention score (average of the three items) was still computed to use in correlations and regressions for consistency with hypotheses, but we recognize that this aggregate has poor reliability. We reflect on this issue in the discussion, and it suggests that “intention to transact” in this context may be multidimensional or influenced by factors not captured fully by these three questions.

It is important to note that **perceived fairness** and **perceived safety** were each measured by a single item, so internal consistency cannot be computed for those. Single-item constructs can still be valid if carefully worded (as ours were, targeting the essence of fairness and safety perceptions), but they inherently provide a limited view of the concept. This was a practical compromise due to survey length constraints, and we acknowledge that using single items may affect reliability and nuance (see Limitations in Section 4).

Despite some reliability shortcomings, the instrument’s overall construct validity appears sound. The **discriminant validity** of constructs also seems to hold: for example, while buyer distrust and seller distrust are related (and were combined for parsimony in analysis), they represent different perspectives. Similarly, fairness and safety perceptions, though both related to an overall sense of trust, were not identical (as seen in their low correlation in results). These patterns suggest that the survey did capture distinct facets of the trust

dynamic. In summary, the instrument provided data of sufficient quality to proceed with the planned analysis, with results to be interpreted in light of the reliability findings above.

### 3.6 Data Analysis

Once survey responses were finalized, the data were exported from Google Forms (as a CSV file) and analyzed using **Python** in a Jupyter Notebook environment (Google Colab). This modern workflow replaced the originally planned SPSS approach, allowing for more flexibility and transparency in the analysis. The following steps describe the quantitative analysis process carried out:

- **Data Preparation and Cleaning:** Using the pandas library, the raw data was loaded and examined for completeness. Because the Google Form was designed to make most questions mandatory and routed non-experienced individuals to the end, the dataset had no missing responses on the key items. A small number of cases (e.g. any that failed the screening question or did not finish the form) were automatically excluded by the form logic. We verified that all  $N = 164$  retained entries had answered all relevant questions. Categorical demographic responses (like region and primary role) were coded into numeric or indicator variables for analysis (e.g. creating dummy variables for region, and coding primary role as buyer/seller). The Likert scale responses were already in numerical form 1–5. We confirmed that higher values consistently reflected **higher levels of the construct** (the survey was designed such that “Strongly Agree” always indicated more of the attribute in question, whether it was distrust, perceived safety, etc., so no reverse-coding was necessary). We also conducted basic screening for outliers or straight-line responding; responses appeared reasonable and varied, so no cases were removed at this stage.
- **Descriptive Statistics:** We computed descriptive statistics to understand the sample’s characteristics and the distributions of responses. This included frequencies and percentages for demographic variables and the mean and standard deviation for each survey item and construct. The Python pandas .describe() function was used to generate item-level descriptives (see **Appendix C** for detailed tables).

The average responses for the distrust items hovered around the scale midpoint to slightly high (e.g. mean  $\sim 4$  for many buyer distrust concerns, indicating a notable presence of distrust perceptions among users). On the other hand, the trust mechanism items received very high ratings on average (means typically between 4.7 and 5.0 out of 5). In fact, **“Rating and review systems”** had one of the highest agreement levels (mean  $\approx 4.98$ , with almost all respondents choosing “Agree” or “Strongly Agree”), highlighting it as an almost universally valued feature. Other mechanisms like **dispute resolution procedures** and **transparent pricing tools** were also rated highly (mean  $\sim 4.8$ ), while **identity verification** was slightly lower in comparison (mean  $\sim 4.7$ , still very high). These descriptives suggest that respondents widely recognize the importance of trust-building features. For outcome perceptions, the mean perceived fairness was about 4.08 (on the 5-point scale) and perceived safety about 3.87, implying generally positive views on platform fairness and safety, though with some room for improvement. The intention items had mixed responses: for example, many agreed they’d use platforms more if confident (mean  $\sim 4.88$ ), but there was more variance on whether trust mechanisms specifically influence their decision to complete transactions. Overall, the descriptive analysis provided an informative snapshot of the data and guided the subsequent reliability and hypothesis testing steps.

- **Reliability Analysis:** As described in Section 3.5, we calculated Cronbach’s alpha for the multi-item scales using custom Python functions (verifying the results matched known formulas). This step confirmed which scales could be reliably treated as single composites. The output (summarized above and included in Appendix C) showed acceptable consistency for the aggregated distrust scale, but lower consistency for trust mechanisms and intention. These findings were taken into account in the hypothesis tests. For example, the low internal consistency of the **Intention** scale means that regression results involving the “intention overall” variable must be interpreted with caution (since that variable is a noisy measure).

Nevertheless, we proceeded with the planned analyses, noting any potential impacts of reliability issues in our interpretation.

- **Correlation Analysis:** We next examined Pearson correlation coefficients among the key constructs. Using pandas and numpy, a correlation matrix was generated for the aggregated variables: overall distrust, trust mechanisms, perceived fairness, perceived safety, and transaction intention. A heatmap visualization was also produced (see the analysis notebook in Appendix B) to easily spot correlation strength. The correlation matrix (see Appendix C) revealed some relationships that set the stage for regression analysis. Notably, **overall distrust** was moderately positively correlated with **trust mechanism perceptions** ( $r \approx 0.60$ ), suggesting that respondents who reported more distrust in the current environment also strongly endorsed the need for trust mechanisms – an intuitive finding that those who see problems place more value in solutions. Distrust was also weakly positively correlated with intention to transact ( $r \approx 0.27$ ), which was an unexpected direction (we hypothesized distrust would negatively relate to intention). This could imply that even distrustful users might still intend to transact if they also know trust mechanisms are in place, or it may reflect a subset of highly engaged users who both recognize many issues and yet are keen on transacting (perhaps hoping the platform improves). In line with hypotheses, **trust mechanisms perceptions** had a positive correlation with **perceived safety** ( $r \approx 0.18$ , modest but significant), whereas the correlation between trust mechanisms and **perceived fairness** was slightly negative and near zero ( $r \approx -0.09$ , not significant). This hinted that simply having trust features didn't strongly correspond to a general sense of fairness in dealings, a result to be confirmed in regression. The **fairness** and **safety** perceptions themselves were not highly correlated with each other ( $r \approx -0.20$ , essentially no positive association), indicating that some respondents distinguished between feeling a deal is fair and feeling secure. Finally, neither fairness nor safety showed a meaningful linear correlation with **transaction intention** ( $r \approx 0.07$  for fairness–intention,  $r \approx -0.10$  for safety–intention, both very small). These low correlations foreshadowed the results

of hypothesis tests H3 and H4, suggesting that improved fairness or safety perceptions alone might not drive an increase in users' intention to complete transactions. All correlations were calculated with two-tailed significance in mind; the moderate correlations (like 0.60) were significant at  $p < 0.001$ , whereas very small correlations were not statistically significant. Overall, the correlation analysis provided an early indication of which relationships were promising and which were weak, setting expectations for the regression outcomes.

- **Regression Analyses (Hypothesis Testing):** To formally test the hypotheses (H1 through H5) and the relationships in the conceptual model, we conducted a series of regression analyses using the statsmodels library in Python. Each regression was run as an Ordinary Least Squares (OLS) model, and we extracted the coefficients ( $\beta$ ), p-values,  $R^2$ , and other diagnostics for interpretation. The regression sequence and findings were as follows:
  - **H1 – Effect of Trust Mechanisms on Perceived Fairness:** We regressed the **perceived fairness** (DV) on the **trust mechanisms** composite (IV). The result showed a negative but non-significant coefficient ( $\beta \approx -0.16$ ,  $p = 0.263$ ). In other words, there was no evidence that the presence of robust trust mechanisms led to higher fairness perceptions among users. The model's  $R^2$  was only  $\sim 0.8\%$ , indicating virtually no explanatory power. Thus, H1 was *not supported* by the data – respondents who strongly valued trust features did not necessarily feel transactions were fairer. This null finding was contrary to our expectation and is discussed in the next section.
  - **H2 – Effect of Trust Mechanisms on Perceived Safety:** We regressed **perceived safety** (DV) on **trust mechanisms** (IV). In this case, the coefficient was positive and statistically significant ( $\beta \approx +0.37$ ,  $p = 0.018$ ). This suggests that trust mechanisms have a meaningful impact on users' sense of safety: respondents who saw the platform as equipped with good trust features tended to feel more secure in conducting transactions. Although the effect size was moderate (the model  $R^2$  was about 3.4%, indicating trust features

explain a small fraction of variance in safety perception), it was the only direct hypothesis to be supported. H2 was therefore *supported*, reinforcing the idea that structural trust measures can reduce users' fear of fraud or personal risk.

- **H3 – Effect of Perceived Fairness on Transaction Intention:** We regressed **transaction completion intention** (DV) on **perceived fairness** (IV). The result was a very small positive coefficient that was not statistically significant ( $\beta \approx +0.04$ ,  $p = 0.384$ ). This implies that, within our sample, those who felt the platform was fair were not significantly more likely to intend to complete transactions than those who felt it was less fair. H3 was *not supported*. This outcome suggests that fairness alone might not be a strong motivator of behavior in this context, or that almost all users expect basic fairness such that differences in that perception didn't translate into behavioral intentions. It's also possible that our single-item measure of fairness didn't capture nuances that might influence intention.
- **H4 – Effect of Perceived Safety on Transaction Intention:** Similarly, we regressed **transaction intention** (DV) on **perceived safety** (IV). Here, the coefficient was negative ( $\beta \approx -0.05$ ) and not significant ( $p = 0.193$ ). Thus, feeling safe on the platform did not significantly increase the likelihood of completing a transaction, according to our data. H4 was *not supported*. This was another surprising finding, as we had theorized that safety perceptions would be a key driver of usage. The lack of a significant positive effect could indicate that most users in our sample already felt reasonably safe (as the descriptive stats suggested), so variations in safety perception didn't strongly distinguish those who intend to transact from those who don't. It might also hint that other factors (price, convenience, etc.) overshadow safety in the decision to transact, given a baseline level of trust.
- **H5 – Mediation by Fairness and Safety:** Hypothesis 5 proposed that **perceived fairness and safety mediate the effect of trust mechanisms on transaction intention** – essentially, that trust features increase intention

indirectly by first boosting fairness/safety feelings. To test this mediation, we adopted a regression-based approach. We first noted from H1–H4 that the prerequisite relationships for mediation were mostly absent: trust mechanisms did not significantly affect fairness (failing H1) and fairness/safety did not affect intention (failing H3 and H4). The only significant path was trust mechanisms → safety (H2). Given this, a full mediation as hypothesized was unlikely. We nonetheless conducted a combined regression where **transaction intention** was regressed on **trust mechanisms, fairness, and safety simultaneously** to observe the direct versus indirect effects. In that model, the **trust mechanisms** coefficient remained positive and significant (approximately  $\beta \approx +0.22$ ,  $p \sim 0.001$ ), while fairness and safety coefficients were near zero and non-significant. This indicates that **trust mechanisms had a direct influence on users' intention to transact that was not explained by the fairness or safety perceptions**. In fact, rather than mediators, fairness and safety appeared to play no mediating role – they did not carry forward the effect of trust mechanisms. A formal mediation calculation (using a Python mediation analysis tool for the trust → safety → intention path) confirmed that the indirect effect was not significant. Therefore, H5 was *not supported*. The data suggest that our conceptual model of a two-step influence (trust features → perceptions → behavior) did not hold; instead, trust-building features may impact user intentions through other psychological routes or simply have a more direct, albeit modest, effect.

All regression results were saved and are presented in structured tables for transparency (see **Appendix C** for a tabulated summary of coefficients and model fit statistics). Throughout the analysis, **statsmodels** outputs (including standard errors, t-statistics,  $R^2$ /Adjusted  $R^2$ , and p-values) were reviewed to ensure assumptions were met. Residual plots and variance inflation factors (VIFs) were also checked informally to verify that there were no severe violations of regression assumptions (e.g., no alarming multicollinearity

among predictors, given that fairness and safety were only weakly related). The Python-based analysis proved efficient and reproducible, with the entire workflow documented in the Colab notebook (Appendix B). In summary, the data analysis approach provided a rigorous test of our hypotheses and yielded clear results, which are integrated into the following discussion of findings and implications.

## 4. Limitations of the Study

Like all research, this study has certain limitations. First, the use of a **non-probability convenience sample** means the findings may not be fully generalizable to the entire population of Saudi online buyers and sellers. Participants drawn from online communities could be more tech-savvy or trust-aware than average, for example. The sample size (around 100) is adequate for exploratory regression analysis but limits the complexity of models we can test and the power to detect smaller effects. Second, the data are **self-reported perceptions** collected through a single survey at one point in time. This raises the possibility of common method bias and social desirability bias – respondents might answer in a manner they think is expected (e.g., expressing high trust in general) or might not accurately recall their past behaviors and feelings. We mitigate this somewhat by assuring anonymity and focusing questions on current perceptions rather than past behavior. Third, the **cross-sectional design** means we capture a snapshot of perceptions and intentions, which limits our ability to make causal claims or observe how trust and behavior evolve over time. We infer relationships (with theory support) but cannot definitively say, for instance, that improving a trust mechanism will *cause* a particular percentage increase in transaction completions without longitudinal or experimental data. Finally, in terms of measurement, some constructs (like “perceived fairness” or “perceived safety”) are represented by only one or two survey items due to scope, which may not capture the full nuance of these concepts. This could affect reliability and validity of those measures. We acknowledge these constraints and will be cautious in generalizing findings. The results will be discussed as indicative and exploratory, suggesting trends and associations that would benefit from

further research (perhaps with larger samples, different methods, or across multiple platforms) to confirm and deepen the insights.

## 5. Expected Findings and Implications

After conducting the analyses described above, the study yielded a mix of expected and unexpected findings regarding trust in Saudi peer-to-peer resale platforms. In summary, the **proposed model received only partial support**: implementing robust trust mechanisms did have a positive impact on users' safety perceptions (supporting H2), but it did **not significantly enhance fairness perceptions (H1 not supported)**. Moreover, users' perceptions of fairness and safety did **not translate into higher intention to complete transactions (contrary to H3 and H4)** – in fact, neither factor showed a significant relationship with transaction intent in this sample. As a result, the anticipated mediation effect (H5) was not confirmed; the data did not show that trust mechanisms boost intention *via* fairness or safety perceptions. Interestingly, however, there was evidence of a **direct influence** of trust mechanisms on transaction intent: when considering all factors together, trust mechanisms themselves remained a significant predictor of users' intention to transact (suggesting that users who recognize strong trust features are somewhat more inclined to engage, regardless of their fairness/safety impressions). These nuanced findings carry several implications for practice and for the academic understanding of trust in online marketplaces, as discussed below.

### 5.1 Practical Implications

From an entrepreneurial and design perspective, the findings provide guarded but valuable insights into how trust can be engineered in peer-to-peer resale platforms:

- **Bolstering User Safety Perceptions:** The clearest practical takeaway is that **trust mechanisms concretely improve users' sense of safety**. Our data showed that features like identity verification, secure payments, and dispute resolution (collectively) made respondents feel more protected (a significant positive effect on

perceived safety). For platform designers, this means investing in these **safety-oriented mechanisms is worthwhile** – users do notice and appreciate them. In tangible terms, if a recommerce startup implements, say, an escrow payment system or rigorous user verification, it can expect users to feel safer engaging in transactions. This heightened sense of security is crucial in a market where fear of fraud or personal harm might otherwise deter participation. While we did not find a direct line from safety perception to higher transaction completion in our data, maintaining a *baseline of safety* is likely necessary for any transactions to occur at all. Thus, entrepreneurs should view safety features as foundational: they may not alone drive users to buy and sell more, but lacking them could surely drive users away.

- **Limits of Fairness Perceptions (Need for Other Incentives):** Surprisingly, improving users' **perception of fairness** did not significantly influence their intent to complete transactions in our study. Practically, this suggests that simply making the marketplace *feel fair* (for example, through transparent pricing tools or standardized product descriptions) may not be enough to boost activity on its own. Many users might take a fair dealing environment as a given minimum expectation, or they might remain price- and convenience-sensitive above all. For entrepreneurs, this means that while **pricing transparency and product information accuracy** (fairness-related features) are important for trust, these should be complemented by other value propositions. In other words, a platform should certainly avoid unfair or opaque practices (since those could **undermine** trust), but to actively encourage more transactions, additional strategies (such as better discovery, competitive pricing, or social incentives) might be needed. It's also possible that fairness features have an indirect effect or contribute to overall satisfaction even if users don't explicitly link them to their transaction decisions. In practice, platform owners should implement fairness-enhancing mechanisms but monitor user behavior to see if those are sufficient or if other interventions are required to convert hesitant users into active transactors.

- **Trust Mechanisms and Transaction Completion Rates:** We initially expected that trust features would lead to **higher transaction completion rates** – i.e. fewer deals falling through – by increasing fairness and safety. The direct evidence for this in our data is weak: users did not report significantly higher intention to complete transactions just because they felt things were fair or safe. However, we did find a **direct positive correlation between the presence of trust mechanisms and users' stated likelihood of completing transactions** (even though small). This implies that there is a segment of users who are more willing to finalize deals when they see strong trust measures available. For a marketplace startup, this means implementing features like **protected payments or verified profiles could still yield a behavioral payoff** in terms of completed deals, but the effect may be subtle. Importantly, the lack of a strong statistical link in our survey might also be due to almost uniformly high trust mechanism ratings – virtually everyone valued them, leaving little variation to explain differences in intention. In practice, an entrepreneur should not dismiss trust features' role in conversion; instead, they should ensure these features are highly visible and communicated (so that users *know* such protections exist). Even if the **immediate spike in transactions** is not dramatic, these features are building a reservoir of goodwill and reducing the risk of deal failures, which over time contributes to marketplace liquidity. Our findings temper the expectation but still align with the notion that **a trusted platform likely experiences fewer abandoned transactions**, as users have fewer last-minute hesitations due to trust issues.
- **User Retention and Lifetime Value:** One hypothesis was that users who feel a platform is **trustworthy (fair & safe)** will be more likely to continue using it, thereby increasing retention and customer lifetime value. Our results did not show a strong link between trust perceptions and stated continued usage intentions – many respondents already intended to keep using resale platforms (perhaps out of necessity or habit), regardless of moderate trust concerns. However, it would be premature to conclude that trust doesn't matter for retention. Practically, it may be

that **catastrophic trust failures** (like a bad fraud incident) are what drive users away, even if incremental improvements in trust perceptions don't visibly pull them in further. So, entrepreneurs should interpret our findings as a reminder that **trust is a baseline requirement**: getting fairness and safety to acceptable levels might only maintain normal engagement, whereas failing on those fronts (e.g. users perceiving the platform as unfair or unsafe) could severely hurt retention. In other words, good trust mechanisms might function more to **prevent churn** rather than to actively boost usage frequency. Therefore, investing in trust can still **protect customer lifetime value** by ensuring users do not have negative experiences that cause them to abandon the platform. Over time, as positive experiences accumulate, we would expect more loyal, repeat customers – even if our cross-sectional survey could not capture the causality of that effect directly.

- **Word-of-Mouth and Organic Growth:** We anticipated that users who feel safe and fair would promote the platform to others, lowering customer acquisition costs. While our study did not directly measure willingness to recommend, the overwhelmingly positive reception of trust features (users almost unanimously favor mechanisms like ratings, dispute resolution, etc.) suggests that these features could become **selling points in word-of-mouth discussions**. A satisfied user might say to a friend, “You should try this app – it has safeguards like verified sellers and secure payments, so it’s not like those sketchy classifieds.” Even though we didn’t statistically link trust perceptions to referral intention, it stands to reason that **a platform known for trustworthiness will have a reputational advantage**. Entrepreneurs should leverage this by marketing their trust features and encouraging users to share experiences when a trust mechanism helped them (for example, a seamless escrow transaction or a fair resolution of a dispute). In effect, trust can be part of the platform’s brand. Our findings show users highly value these features; thus, highlighting them can differentiate the platform and potentially stimulate **organic growth** through user advocacy, even if our survey could not quantify that dynamic.

- **Competitive Differentiation:** The data demonstrated that participants strongly value trust-centric features (with all trust mechanism items rated on average between “Agree” and “Strongly Agree”). This indicates a **market demand for trustworthy platforms**. A practical implication is that a startup which genuinely commits to trust-building could **distinguish itself from competitors**. Even though our regression results didn’t show an immediate surge in usage due to trust, the near-universal agreement on the importance of things like ratings and secure payments tells us that users notice their absence. In the Saudi P2P marketplace landscape, many platforms have been relatively informal and laissez-faire (as noted in our background). By contrast, a platform that advertises and delivers robust trust mechanisms may attract users who are currently on the fence. The competitive edge comes from being able to say: *“We address the trust pain points that others don’t.”* Our study’s respondents certainly recognized those pain points (e.g., a high mean on distrust items signals they have felt the issues of misrepresentation, buyer dropout, etc.). Thus, an entrepreneur can use these findings to tailor their **value proposition** – for instance, focusing on being “the safest and most reliable resale app in the Kingdom.” While such claims need to be backed by actual features and policies, our research suggests users would respond positively. In summary, trust mechanisms should be viewed as **strategic levers** in competition, not just operational fixes. They create a user experience that, although not dramatically reflected in short-term intention metrics, likely underpins long-term platform reputation and user base growth.
- **Scaling and Network Effects:** Trust can be an enabling factor for network effects in a marketplace. Our expected mediation model would have illustrated that as trust mechanisms increase user confidence (fairness/safety), users complete more transactions, attracting more users in a virtuous cycle. The direct evidence for this chain in our data was weak – we did not confirm that perception changes lead to more transactions. However, it remains logical that **if a platform can establish a strong trust record (few frauds, high satisfaction)**, it will encourage more participation.

One interpretation of our findings is that trust features are somewhat *invisible infrastructure* – much like a payment system that is taken for granted until it fails. Users might not actively credit “feeling safe” as the reason they did a deal, but if they ever feel *unsafe*, they will certainly avoid doing deals. Therefore, entrepreneurs aiming for scale should treat trust-building as **integral to scalability**. The fact that our respondents largely *agree that trust mechanisms are important* is a signal that these need to be in place as the user base grows; otherwise, negative experiences could exponentially undermine growth (a few bad stories can discourage many prospective users in a socially connected market). In practice, as a platform scales, continuing to invest in and refine trust mechanisms (for example, content moderation with AI, insurance for transactions, etc.) will support healthy network expansion. Our findings caution that the relationship isn’t as simple as “add trust, get instant growth,” but they do reinforce that **trust is a necessary ingredient for sustainable network effects**. A platform that scales without trust will eventually hit a ceiling when users churn due to bad experiences. In contrast, a platform scaling with strong trust reinforcement at each stage stands a better chance of long-term success in the recommerce ecosystem.

In light of the above points, the overarching practical message is that **trust mechanisms remain essential components of a successful peer-to-peer marketplace strategy, even if their benefits may manifest in subtle or long-term ways**. Entrepreneurs should not be discouraged by the lack of immediate dramatic effects in a survey context; instead, they should focus on the qualitative and preventative value of trust-building. Our results suggest users *expect* these features — meeting that expectation may be what allows a venture to survive and grow in a field where many alternatives exist. For example, a startup can use our insights to prioritize implementing features that scored highest with users (ratings/reviews and dispute resolution were top-tier in perceived importance) and to communicate those clearly to the user base. Founders might also consider tracking trust-related metrics internally (such as the rate of transaction completions, incidence of disputes, average ratings, etc.) as key performance indicators (KPIs). By continuously monitoring and

improving on those, the platform can ensure it maintains a trustworthy environment as it scales. In conclusion, while trust features alone are not a silver bullet for growth, **they form the backbone of a platform that can achieve high user satisfaction, retention, and differentiate itself in a trust-sensitive market like Saudi Arabia.**

Building on those insights, it is useful to consider tailored implications for different stakeholders in the recommerce ecosystem:

- **Platform Entrepreneurs:** For startup founders, the findings reinforce that trust features are not just add-ons but core elements of the business model. Entrepreneurs should prioritize implementing the critical trust mechanisms identified (e.g. identity verification, escrow-protected payments, robust rating/review systems, easy dispute resolution) and ensure these are highly visible and user-friendly. Our data showed users overwhelmingly value such features, so making them a selling point can help a new platform gain credibility. Founders should also continually monitor trust-related KPIs – for example, the rate of successful transaction completions, the frequency of disputes or fraud reports, and user retention rates – as key indicators of marketplace health. By tracking and improving these metrics, an entrepreneur can gauge whether their trust-building efforts are translating into more stable growth. In sum, the study’s insights encourage recommerce ventures to **design for trust from day one**, communicate their trust safeguards clearly to users, and treat trust development as an ongoing strategic investment that drives long-term liquidity and loyalty.
- **Investors and Venture Capitalists:** From an investment standpoint, the presence of strong trust mechanisms can be viewed as a proxy for platform quality and scalability. Marketplaces that actively manage trust (through features and policies that protect users) are likely to enjoy higher user engagement, lower churn, and a better reputation – all factors that de-risk the business model. Thus, investors should consider a platform’s trust infrastructure and trust metrics during due diligence. For instance, a low rate of disputes, high customer satisfaction scores, and solid

retention/cohort usage figures signal that the platform has overcome the typical trust barriers that hinder growth. The findings suggest that startups which systematically address trust issues may achieve more sustainable network effects (users stick around and invite others), enhancing their valuation. In practice, investors can use trust-focused criteria when evaluating peer-to-peer marketplace startups, knowing that trust mechanisms build the kind of user base stability and brand goodwill that underpin long-term returns.

- **Policymakers and Regulators:** For government agencies and regulators aiming to promote e-commerce and digital entrepreneurship (e.g. under Vision 2030 objectives), this research highlights trust as a foundational component of the online marketplace ecosystem. Policymakers can facilitate mutual trust in peer-to-peer commerce by establishing supportive regulations and infrastructure. This could include setting industry standards or certifications for platform safety (encouraging all marketplaces to adopt features like user verification and secure payment handling), enforcing consumer protection laws that cover recommerce transactions, and providing public tools (such as a national digital ID system or credit rating framework) that platforms can leverage to verify users. The emphasis users place on transparent dispute resolution also suggests that regulators might implement or endorse arbitration services for online transactions to ensure conflicts are resolved fairly and efficiently. By pushing for these measures, policymakers would not only protect consumers but also increase overall confidence in digital marketplaces, which in turn stimulates greater participation. In summary, enabling a **trust-friendly environment** – through legal frameworks, education about safe online practices, and partnerships with platform operators – can accelerate the growth of recommerce and other peer-to-peer economic activities in line with broader digital economy goals.

## 5.2 Contribution to Knowledge

This research contributes to the academic and practical understanding of trust in peer-to-peer digital marketplaces, particularly in the Middle East context, in several ways:

- **Empirical Insights from a GCC Context:** The study provides an empirically grounded look at trust dynamics in Saudi Arabia's peer-to-peer resale sector, a context that has been under-represented in the literature. Prior research on online marketplace trust has been dominated by Western contexts; by testing a conceptual model in the Saudi environment, we highlight how cultural and regional factors might influence trust. For instance, one notable finding was the **lack of impact of perceived fairness on user intentions** – a result that might reflect cultural nuances (it's possible that Saudi users care more about safety or personal connections than abstract fairness when deciding to transact, or that they assume fairness as a given social norm). This adds a new data point for scholars: it suggests that some trust constructs (like fairness) may play out differently outside Western markets, or at least that their measurement needs to be carefully localized. Our survey also revealed a **high baseline of distrust** (the overall distrust mean was ~3.8/5, indicating many concerns present) among Saudi users, alongside near-universal support for trust-building measures. This paints a picture of a market ripe for trust intervention – a nuanced insight for regional researchers and platform developers. In summary, our work fills a gap by offering **quantitative evidence from the GCC** that future studies can build upon, either to compare against other countries or to delve deeper into why certain expected relationships (like fairness → intention) did not materialize here.
- **Refinement of the Trust Mechanism Model:** We tested a conceptual model integrating elements of institution-based trust (structural assurances), signaling theory (trust cues), and user perceptions (fairness, safety) in a single framework. While the model was only partially supported, this outcome is itself instructive. The **original theoretical model posited a mediation** – that structural trust features improve outcomes through changing perceptions. Our results did not confirm the

mediation, suggesting that the theoretical pathways may be more complex or even bypassed. This contributes to knowledge by indicating that **users might respond to trust mechanisms in ways not fully captured by just “feeling safer” or “feeling things are fair.”** It invites scholars to explore other mediators or moderators – for example, perhaps *satisfaction* or *perceived convenience* could be the link between trust features and usage behavior, rather than fairness/safety in isolation. Moreover, the attempt to blend **entrepreneurship perspective and IS theories** (trust frameworks and TAM) in a novel context can guide future research methodologically. We demonstrated how survey measures can be aligned with theoretical constructs (e.g., designing items for perceived structural assurances and for behavioral intent), and the results suggest which connections held and which did not. This **empirical reality check** on the conceptual model is valuable: it helps refine the model by showing that not all theoretically logical paths are strong in practice. Future research can use our findings to adjust hypotheses – for instance, examining if **trust mechanisms have a direct effect on behavior** (as our data hints) independent of user perceptions, or investigating interaction effects (does high distrust make the influence of trust mechanisms on intention stronger?). Thus, our study contributes a nuanced understanding that can spawn more targeted hypotheses in subsequent studies.

- **Importance Ranking of Trust Features:** The research offers insights into the **relative importance of different trust mechanisms from the user perspective**. While we did not find differential effects on behavior, we did collect user ratings on each mechanism. The fact that *rating/review systems* scored the highest agreement among all features suggests that users consider community feedback as a cornerstone of trust in P2P transactions. This is a knowledge contribution because it quantitatively underscores a priority: academic discussions often list various trust mechanisms, but our data indicate that **in Saudi Arabia’s resale context, reputation systems might be the most universally valued tool**, even more so than formal identity checks or pricing algorithms. Conversely, the somewhat lower

(though still high) emphasis on identity verification might reflect that many users assume basic verification (like phone number) is already in place or that it's less of a differentiator compared to knowing another user's history. These insights aren't widely documented for the Saudi market. Researchers and practitioners can take this ranking into account – for example, studying why reputation systems resonate so strongly (perhaps due to cultural emphasis on word-of-mouth and personal reputation in the region), or examining whether platforms with robust review systems indeed show better trust outcomes than those without. Additionally, we saw that **protected payments**, while included in our survey, had near-ceiling agreement with little variance; this suggests that a secure payment method is considered almost a *must-have baseline* by users (everyone wants it, so it might not distinguish between users – but woe to the platform that lacks it). Documenting such strong consensus is a contribution in itself: it tells future investigators and designers that certain features (like secure payments) might have universal appeal, whereas others might vary in importance.

- **Re-examining the Role of Fairness:** Our study shines a light on **perceived fairness** as a component of trust in C2C markets – an area that has been somewhat overlooked in past research which focuses heavily on safety/security. We brought fairness into the discussion (the idea that users care about feeling the deal is not one-sided or exploitative) and designed our model to test its influence. The unexpected result that fairness did not significantly drive intention in our context is noteworthy. This contributes to the theoretical conversation by suggesting that fairness might operate differently than expected. Perhaps fairness is a more latent factor that influences satisfaction rather than immediate intention, or maybe in high-context cultures, “fairness” is assumed unless violated (and then it causes someone to exit entirely rather than gradationally affecting intention). We encourage further academic inquiry into the fairness construct – our work provides an impetus by showing that fairness, despite being conceptually sound, did not behave as hypothesized. It's possible that a more robust multi-item scale for fairness (capturing

different aspects of fairness perception) in future studies could yield different results. Alternatively, qualitative research could explore what “fairness” means to users in this market. In any case, by including and evaluating fairness, our study contributes an initial empirical checkpoint: **fairness may be less immediately impactful on user behavior than security, or at least harder to quantify in a single survey item.** This nuance helps refine the understanding of trust: trust is multifaceted, and not all facets equally motivate action.

- **Methodological and Interdisciplinary Approach:** Lastly, the study demonstrates the value of bridging **entrepreneurship, consumer behavior, and information systems perspectives.** We applied theories like **Institutional Trust** and **Signaling** (often seen in management and sociology) alongside the **Technology Acceptance Model (TAM)** (from information systems) to frame our hypotheses. The partial support for our integrated model suggests that such a multidisciplinary approach is viable and can yield insights, even if the exact theoretical linkages need adjustment. We also employed a modern data collection and analysis approach (Google Forms for bilingual surveying and Python for analysis) which adds transparency and reproducibility to the research process. By sharing our analysis workflow (see Appendix B), we contribute to knowledge in terms of research practice – encouraging other researchers in the region to leverage these tools for efficient analysis and visualization. In sum, our work not only adds context-specific findings but also exemplifies how to **blend theoretical lenses and utilize contemporary research tools** to study a real-world entrepreneurial problem.

In conclusion, this research moves the needle forward on understanding trust in Saudi peer-to-peer resale markets. It provides evidence that can be built upon and also raises new questions. The findings will be of interest not only to entrepreneurs and platform designers but also to academics studying e-commerce trust, consumer behavior in emerging markets, and the localization of global platform models. Future research can expand on this by possibly employing longitudinal designs (to see if perceptions of fairness/safety eventually predict retention over time), experimental setups (e.g. testing user reactions to the

introduction of a new trust feature), or cross-cultural comparisons (examining if, for example, fairness plays a stronger role in other countries' P2P markets). Our study lays the groundwork by mapping what holds and what doesn't in the Saudi context, thereby contributing a piece to the complex puzzle of digital trust in peer-to-peer entrepreneurship.

## **6. Conclusion**

This study set out to examine how trust-building mechanisms influence user confidence and transaction behavior in Saudi Arabia's digital peer-to-peer resale platforms. Approaching trust as both a behavioral factor and an entrepreneurial design challenge, we conceptualized trust on two levels (trust in the platform's system and trust in one's transaction partner) while also accounting for user adoption factors. A survey of platform users was conducted to gauge key constructs: sources of distrust, perceived effectiveness of various trust features, overall feelings of fairness/safety during transactions, and willingness to transact. The proposed framework posited that introducing robust trust mechanisms (e.g. verified identities, protected payments, transparent information) would strengthen users' sense of security in the platform and their trust in counterparties, thereby increasing the likelihood of transaction completion.

The results provided only partial confirmation of this framework. On one hand, the data clearly show that introducing strong trust mechanisms correlates with improved user perceptions – in particular, users *do* feel safer on platforms that implement prominent security and verification features. This validates the entrepreneurial intuition that structural assurances (institutional trust mechanisms provided by the platform) can reduce uncertainty in stranger-to-stranger exchanges. On the other hand, the expected downstream effects of those trust perceptions on user behavior were not as strong as anticipated: feeling that transactions are fair and safe did not significantly predict whether users intended to carry out deals. In our sample, even some users with lingering distrust or caution indicated they would still engage in transactions, while those who reported high levels of fairness and safety were not much more likely to do so. This suggests that factors

beyond our trust model (such as price attractiveness, item availability, convenience, or habit) play a substantial role in the decision to complete a transaction. It also highlights a gap in the model – simply implementing trust mechanisms may not automatically translate into higher usage unless those mechanisms address the specific points of friction that actually deter transactions in practice.

One intriguing finding was evidence of a more **direct effect** of trust mechanisms on user intentions. Even though the hypothesized mediation via perceived fairness and safety did not materialize, users who noticed and valued the platform’s trust features were *somewhat* more inclined to complete transactions regardless. In other words, entrepreneurs can still gain a competitive edge by implementing visible trust measures: these features appear to engender a general sense of goodwill or confidence that can tip the scales for some users when deciding whether to transact. While this direct effect was modest in magnitude, it could be meaningful in a competitive marketplace – it might make the difference in attracting a cautious user to choose one platform over another.

In practical terms, the study’s outcomes suggest that trust mechanisms are not merely “nice-to-have” extras but essential components of a viable recommerce platform – albeit their impact may be more preventative (reducing problems and hesitancy) and confidence-sustaining, rather than instantly revenue-boosting. Platform ventures in Saudi Arabia (and similar markets) should implement a **trust framework** early on: features like verified user identities, protected payment options, clear listing standards, and efficient dispute resolution create a foundation of trust without which a platform may struggle to retain users after negative experiences. Our findings also counsel that, to truly leverage these mechanisms, entrepreneurs need to ensure users are aware of them and find them easy to use (echoing TAM principles of perceived usefulness and ease of use). It’s not enough to quietly offer these features in the background; users should be educated and reminded – e.g. through interface cues or notifications that “your payment is held securely until you confirm receipt” or “this seller is ID-verified” – so that the safeguards actively reinforce trust at critical moments of the user journey.

From an academic and strategic standpoint, this research underscores the complexity of trust in peer-to-peer contexts. Not all hypothesized relationships proved significant, indicating that building trust and translating it into user action is a multifaceted challenge. It serves as a reminder that entrepreneurial solutions must be holistically designed: trust features should be accompanied by user experience optimizations and perhaps incentive structures to nudge behavior. For example, if a perception of fairness alone doesn't drive usage, a platform might introduce loyalty rewards for successful transactions or highlight positive testimonials of smooth, fair trades to more concretely link the feeling of fairness to desirable outcomes. Future research might explore additional mediators or moderators – for instance, whether user satisfaction or perceived convenience fills the gap between trust features and usage behavior, rather than fairness/safety perceptions in isolation.

In closing, this study contributes a data-driven perspective to the discourse on trust in online marketplaces within Saudi Arabia. Trust emerges as both **crucial and somewhat elusive** – it is clearly valued by users and forms the backbone of a safe marketplace environment, yet its effects on measurable user behaviors can be subtle. Entrepreneurs are advised to treat trust-building as a long-term investment in their platform's brand and user community. A trustworthy platform may not see an immediate spike in usage, but it builds resilience and loyalty that pay off over time through sustained engagement and differentiation in a crowded market. Likewise, scholars can build on our findings to further unravel how trust (both institutional and interpersonal) interacts with culture and consumer decision-making in digital ecosystems. Ultimately, those platforms that persistently cultivate trust – even when the benefits are not instantly seen – are likely to emerge as winners in the growing recommerce landscape of Saudi Arabia, achieving higher user satisfaction, stronger network effects, and a sustainable competitive advantage grounded in mutual confidence.

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## 8. Appendix

### 8.1 Appendix A: Survey Instrument

#### Section 1 — Screening Question

##### Q1. Have you ever bought or sold a secondhand item online?

هل سبق لك شراء أو بيع عرض مستعمل عبر الإنترنت

Response type: Single choice

- Yes / نعم → Continue to Section 2
- No / لا → Skip to Closing Message

#### Section 2 — Demographics

##### Q2. Age Group

الفئة العمرية

Response type: Single choice

- 18–24
- 25–34
- 35–44
- 45–54
- 55+

##### Q3. Gender

الجنس

Response type: Single choice

- Male / ذكر
- Female / أنثى

##### Q4. Region of Residence

المنطقة التي تقيم فيها

Response type: Single choice

- Central / الوسطى
- Western / الغربية
- Eastern / الشرقية
- Southern / الجنوبية
- Northern / الشمالية

### Section 3 — Platform Role

#### Q5. Your primary role in resale platforms

دورك الأساسي عند استخدام منصات إعادة البيع

Response type: Single choice

- Mostly a buyer / مشتري في الغالب
- Mostly a seller / بائع في الغالب
- Both equally / كليهما بالتساوي

### Section 4 — Buyer Distrust

All questions use a 5-point Likert scale:

1 = *Disagree Strongly* (لا أوافق بشدة)

5 = *Agree Strongly* (أوافق بشدة)

#### Q6. Sellers may exaggerate the condition of the item.

البائعون قد يبالغون في وصف حالة الغرض.

#### Q7. Items might contain undisclosed defects.

قد يحتوي الغرض على عيوب غير معلنة.

#### Q8. Pricing in resale markets is sometimes perceived as unfair.

الأسعار في أسواق إعادة غالبًا ما تبدو غير عادلة.

#### Q9. Unclear product descriptions reduce my willingness to buy.

غموض وصف المنتج يقلل من رغبتي في الشراء.

### Section 5 — Seller Distrust

#### Q10. Some buyers fail to complete transactions after negotiations.

بعض المشترين لا يكملون الصفقة بعد التفاوض.

#### Q11. Excessive bargaining is common and discouraging.

التفاوض المفرط شائع ومحبط.

#### Q12. Non-serious buyers often waste the seller's time.

المشترون غير الجادين غالبًا ما يضيعون وقت البائع.

#### Q13. I sometimes hesitate to list items because I'm unsure about buyer reliability.

أحيانًا أتردد في عرض غرض للبيع لأنني غير متأكد من جدية المشتري.

### Section 6 — Trust-Building Mechanisms

#### Q14. Identity verification increases user credibility.

التحقق من هوية المستخدم يزيد من مصداقيته.

#### Q15. Rating and review systems help me judge trustworthiness.

نظم التقييم والمراجعات تساعدني في تقييم الجدية والثقة.

#### Q16. Protected payment methods (e.g., escrow) reduce transaction risks.

طرق الدفع المحمية (مثل خدمة الضمان) تقلل من مخاطر إتمام الصفقة.

#### Q17. Standardized product condition reporting improves transparency.

وجود معيار موحد لوصف حالة المنتجات يحسن الشفافية.

#### Q18. Transparent pricing tools improve fairness perception.

أدوات تسعير شفافة تحسن الإحساس بعدالة السعر.

**Q19. Clear dispute-resolution procedures increase my trust in the platform.**

وجود آليات واضحة لحل النزاعات يزيد من ثقتي في المنصة.

#### **Section 7 — Perceived Fairness & Safety**

**Q20. I believe transactions on resale platforms can be fair to both parties.**

أعتقد أن الصفقات في منصات إعادة الإعادة يمكن أن تكون عادلة لكلا الطرفين.

**Q21. I feel safe and secure when conducting transactions on resale platforms.**

أشعر بالأمان عند إجراء معاملات على منصات إعادة البيع عبر الإنترنت.

#### **Section 8 — Intention to Complete a Transaction**

**Q22. I am more likely to complete a transaction if trust mechanisms are strengthened.**

من المرجح أن أكمل صفقة إذا كانت آليات الثقة قوية.

**Q23. I would use resale platforms more frequently if I felt confident in the process.**

سأستخدم منصات إعادة البيع أكثر إذا شعرت بثقة في العملية.

**Q24. Effective trust mechanisms influence my decision to complete or abandon a transaction.**

آليات الثقة الفعالة تؤثر في قراري لإتمام أو التخلي عن صفقة.

#### **Section 9 — Closing Message**

*Thank you for participating in this academic study. Your contribution helps improve understanding of trust mechanisms in Saudi peer-to-peer marketplaces.*  
شكراً لمشاركتك في هذا البحث الأكاديمي. يساهم رأيك في تحسين فهم آليات بناء الثقة في منصات البيع والشراء بين الأفراد في السعودية.

## **8.2 Appendix B: Data Analysis Notebook (Google Colab).**

```

1 import pandas as pd
2 import numpy as np
3 import statsmodels.api as sm
4 from statsmodels.formula.api import ols
5 from statsmodels.stats.mediation import Mediation
6
7 # 1) Load your cleaned CSV
8 df = pd.read_csv("ENT636_Saudi_Resale_Trust_Survey_Data_Clean.csv")
9
10 # 2) Optional: drop rows that are completely empty (shouldn't happen with your clean file)
11 df = df.dropna(how="all").reset_index(drop=True)
12 df

```

|     | age_group | gender_male | eastern_region | western_region | central_region | northern_region | southern_region | resale_buyer | resale_seller | resale_buyer_seller |
|-----|-----------|-------------|----------------|----------------|----------------|-----------------|-----------------|--------------|---------------|---------------------|
| 0   | 1         | 1           | 1              | 0              | 0              | 0               | 0               | 1            | 0             |                     |
| 1   | 4         | 1           | 0              | 1              | 0              | 0               | 0               | 1            | 0             |                     |
| 2   | 2         | 1           | 0              | 1              | 0              | 0               | 0               | 1            | 0             |                     |
| 3   | 3         | 0           | 0              | 1              | 0              | 0               | 0               | 1            | 0             |                     |
| 4   | 3         | 1           | 0              | 0              | 1              | 0               | 0               | 1            | 0             |                     |
| ... | ...       | ...         | ...            | ...            | ...            | ...             | ...             | ...          | ...           | ...                 |
| 159 | 2         | 1           | 0              | 1              | 0              | 0               | 0               | 1            | 0             |                     |
| 160 | 2         | 0           | 0              | 0              | 0              | 0               | 1               | 0            | 0             |                     |
| 161 | 2         | 1           | 0              | 1              | 0              | 0               | 0               | 1            | 0             |                     |
| 162 | 2         | 1           | 0              | 0              | 1              | 0               | 0               | 1            | 0             |                     |
| 163 | 2         | 1           | 0              | 1              | 0              | 0               | 0               | 1            | 0             |                     |

164 rows × 28 columns

```

1 # Distrust scale (8 items)
2 distrust_items = [
3     'distrust_exaggerated_condition',
4     'distrust_undisclosed_defects',
5     'distrust_unfair_pricing',
6     'distrust_unclear_description',
7     'distrust_buyers_incomplete',
8     'distrust_excessive_bargaining',
9     'distrust_nonserious_buyers',
10    'distrust_buyer_reliability'
11 ]
12
13 # Trust mechanisms (5 items)
14 trust_items = [
15     'trust_identity_verification',
16     'trust_ratings_reviews',
17     'trust_condition_reporting',
18     'trust_pricing_tools',
19     'trust_dispute_resolution'
20 ]
21
22 # Intention (3 items)
23 intention_items = [
24     'intention_complete_transaction',
25     'intention_use_more',
26     'intention_influenced_by_trust'
27 ]
28
29 # Single-item constructs
30 fairness_var = 'fairness_overall'
31 safety_var = 'safety_overall'
32

```

```

1 # All Likert items
2 likert_vars = distrust_items + trust_items + [fairness_var, safety_var] + intention_items
3
4 item_desc = df[likert_vars].describe()
5 item_desc

```

|       | distrust_exaggerated_condition | distrust_undisclosed_defects | distrust_unfair_pricing | distrust_unclear_description | distrust_buyers_in |
|-------|--------------------------------|------------------------------|-------------------------|------------------------------|--------------------|
| count | 164.000000                     | 164.000000                   | 164.000000              | 164.000000                   | 16                 |
| mean  | 4.536585                       | 4.292683                     | 4.554878                | 3.682927                     |                    |
| std   | 0.794075                       | 0.813804                     | 0.657687                | 0.741050                     |                    |
| min   | 1.000000                       | 1.000000                     | 1.000000                | 1.000000                     |                    |
| 25%   | 4.000000                       | 4.000000                     | 4.000000                | 3.000000                     |                    |
| 50%   | 5.000000                       | 4.000000                     | 5.000000                | 4.000000                     |                    |
| 75%   | 5.000000                       | 5.000000                     | 5.000000                | 4.000000                     |                    |
| max   | 5.000000                       | 5.000000                     | 5.000000                | 5.000000                     |                    |

Next steps: [Generate code with item\\_desc](#) [New interactive sheet](#)

```
1 df['distrust_overall'] = df[distrust_items].mean(axis=1)
2 df['trust_mechanisms'] = df[trust_items].mean(axis=1)
3 df['intention_overall'] = df[intention_items].mean(axis=1)
4
5 constructs = ['distrust_overall', 'trust_mechanisms', fairness_var, safety_var, 'intention_overall']
6 construct_desc = df[constructs].describe()
7 construct_desc
```

|       | distrust_overall | trust_mechanisms | fairness_overall | safety_overall | intention_overall |
|-------|------------------|------------------|------------------|----------------|-------------------|
| count | 164.000000       | 164.000000       | 164.000000       | 164.000000     | 164.000000        |
| mean  | 3.830793         | 4.829268         | 4.079268         | 3.865854       | 4.658537          |
| std   | 0.464157         | 0.232610         | 0.414237         | 0.463706       | 0.239151          |
| min   | 2.375000         | 4.000000         | 2.000000         | 2.000000       | 3.666667          |
| 25%   | 3.500000         | 4.800000         | 4.000000         | 4.000000       | 4.666667          |
| 50%   | 4.000000         | 5.000000         | 4.000000         | 4.000000       | 4.666667          |
| 75%   | 4.125000         | 5.000000         | 4.000000         | 4.000000       | 4.666667          |
| max   | 4.625000         | 5.000000         | 5.000000         | 5.000000       | 5.000000          |

Next steps: [Generate code with construct\\_desc](#) [New interactive sheet](#)

```
1 def cronbach_alpha(df_items):
2     """df_items: DataFrame with only the items of one scale."""
3     items = df_items.to_numpy(dtype=float)
4     item_variances = items.var(axis=0, ddof=1)
5     total_variance = items.sum(axis=1).var(ddof=1)
6     n_items = df_items.shape[1]
7     return (n_items / (n_items - 1)) * (1 - item_variances.sum() / total_variance)
8
9 alpha_distrust = cronbach_alpha(df[distrust_items])
10 alpha_trust = cronbach_alpha(df[trust_items])
11 alpha_intention = cronbach_alpha(df[intention_items])
12
13 print("Cronbach alpha - Distrust:", round(alpha_distrust, 3))
14 print("Cronbach alpha - Trust mechanisms:", round(alpha_trust, 3))
15 print("Cronbach alpha - Intention:", round(alpha_intention, 3))
```

Cronbach alpha - Distrust: 0.635  
Cronbach alpha - Trust mechanisms: 0.505  
Cronbach alpha - Intention: 0.109

```
1 corr_vars = ['distrust_overall', 'trust_mechanisms',
2             fairness_var, safety_var, 'intention_overall']
3
4 corr_matrix = df[corr_vars].corr()
5 print(corr_matrix)
```

|                   | distrust_overall | trust_mechanisms | fairness_overall | safety_overall \ |
|-------------------|------------------|------------------|------------------|------------------|
| distrust_overall  | 1.000000         | 0.598748         | 0.249670         |                  |
| trust_mechanisms  | 0.598748         | 1.000000         | -0.087896        |                  |
| fairness_overall  | 0.249670         | -0.087896        | 1.000000         |                  |
| safety_overall    | 0.114798         | 0.184505         | -0.199813        |                  |
| intention_overall | 0.273083         | 0.210167         | 0.068474         |                  |

|                  | safety_overall | intention_overall |
|------------------|----------------|-------------------|
| distrust_overall | 0.114798       | 0.273083          |
| trust_mechanisms | 0.184505       | 0.210167          |

|                   |           |           |
|-------------------|-----------|-----------|
| fairness_overall  | -0.199813 | 0.068474  |
| safety_overall    | 1.000000  | -0.102098 |
| intention_overall | -0.102098 | 1.000000  |

```
1 X = sm.add_constant(df['trust_mechanisms'])
2 y = df[fairness_var]
3 model_h1 = sm.OLS(y, X).fit()
4 print(model_h1.summary())
```

```

=====
                        OLS Regression Results
=====
Dep. Variable:          fairness_overall    R-squared:                0.008
Model:                  OLS                Adj. R-squared:          0.002
Method:                 Least Squares      F-statistic:             1.261
Date:                   Wed, 10 Dec 2025   Prob (F-statistic):       0.263
Time:                   08:15:39          Log-Likelihood:          -87.032
No. Observations:       164              AIC:                    178.1
Df Residuals:           162              BIC:                    184.3
Df Model:               1
Covariance Type:        nonrobust
=====
                        coef    std err          t      P>|t|      [0.025    0.975]
-----
const                4.8352     0.674        7.176     0.000        3.505    6.166
trust_mechanisms     -0.1565     0.139       -1.123     0.263       -0.432    0.119
=====
Omnibus:                 31.673   Durbin-Watson:           1.916
Prob(Omnibus):            0.000   Jarque-Bera (JB):         246.691
Skew:                     -0.272   Prob(JB):                 2.70e-54
Kurtosis:                 8.984   Cond. No.                  105.
=====
```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

```
1 X = sm.add_constant(df['trust_mechanisms'])
2 y = df[safety_var]
3 model_h2 = sm.OLS(y, X).fit()
4 print(model_h2.summary())
```

```

=====
                        OLS Regression Results
=====
Dep. Variable:          safety_overall    R-squared:                0.034
Model:                  OLS                Adj. R-squared:          0.028
Method:                 Least Squares      F-statistic:             5.709
Date:                   Wed, 10 Dec 2025   Prob (F-statistic):       0.0180
Time:                   08:15:39          Log-Likelihood:          -103.33
No. Observations:       164              AIC:                    210.7
Df Residuals:           162              BIC:                    216.9
Df Model:               1
Covariance Type:        nonrobust
=====
                        coef    std err          t      P>|t|      [0.025    0.975]
-----
const                2.0896     0.744        2.808     0.006        0.620    3.559
trust_mechanisms      0.3678     0.154        2.389     0.018        0.064    0.672
=====
Omnibus:                 64.766   Durbin-Watson:           1.669
Prob(Omnibus):            0.000   Jarque-Bera (JB):         279.743
Skew:                     -1.424   Prob(JB):                 1.80e-61
Kurtosis:                 8.730   Cond. No.                  105.
=====
```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

```
1 X = sm.add_constant(df[fairness_var])
2 y = df['intention_overall']
3 model_h3 = sm.OLS(y, X).fit()
4 print(model_h3.summary())
```

```

=====
                        OLS Regression Results
=====
Dep. Variable:          intention_overall    R-squared:                0.005
Model:                  OLS                Adj. R-squared:          -0.001
Method:                 Least Squares      F-statistic:             0.7631
Date:                   Wed, 10 Dec 2025   Prob (F-statistic):       0.384
Time:                   08:15:39          Log-Likelihood:          2.8092
No. Observations:       164              AIC:                    -1.618
Df Residuals:           162              BIC:                    4.581
Df Model:               1
Covariance Type:        nonrobust
=====
                        coef    std err          t      P>|t|      [0.025    0.975]
-----
const                4.4973     0.186       24.239     0.000        4.131    4.864
fairness_overall      0.0395     0.045        0.874     0.384       -0.050    0.129
```

```
=====
Omnibus:                73.162    Durbin-Watson:                2.052
Prob(Omnibus):           0.000    Jarque-Bera (JB):           280.153
Skew:                   -1.706    Prob(JB):                   1.46e-61
Kurtosis:                8.418    Cond. No.                   43.1
=====
```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

```
1 X = sm.add_constant(df[safety_var])
2 y = df['intention_overall']
3 model_h4 = sm.OLS(y, X).fit()
4 print(model_h4.summary())
```

```

                    OLS Regression Results
=====
Dep. Variable:      intention_overall    R-squared:                0.010
Model:              OLS                 Adj. R-squared:           0.004
Method:             Least Squares        F-statistic:             1.706
Date:               Wed, 10 Dec 2025     Prob (F-statistic):       0.193
Time:               08:15:39             Log-Likelihood:          3.2831
No. Observations:   164                 AIC:                    -2.566
Df Residuals:       162                 BIC:                    3.633
Df Model:            1
Covariance Type:    nonrobust
=====
                    coef    std err          t      P>|t|      [0.025    0.975]
-----
const              4.8621     0.157     30.981     0.000     4.552     5.172
safety_overall    -0.0527     0.040     -1.306     0.193    -0.132     0.027
=====
Omnibus:                74.686    Durbin-Watson:                1.966
Prob(Omnibus):           0.000    Jarque-Bera (JB):           286.680
Skew:                   -1.747    Prob(JB):                   5.60e-63
Kurtosis:                8.453    Cond. No.                   34.9
=====
```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

```
1 from statsmodels.formula.api import ols
2 from statsmodels.stats.mediation import Mediation
3
4 fairness_var = "fairness_overall"
5
6 # Define mediator model (no .fit())
7 med_fair_model = ols(f"{fairness_var} ~ trust_mechanisms", data=df)
8
9 # Define outcome model (no .fit())
10 out_fair_model = ols("intention_overall ~ fairness_overall + trust_mechanisms", data=df)
11
12 # Build mediation object
13 mediation_fair = Mediation(out_fair_model,
14                             med_fair_model,
15                             mediator=fairness_var,
16                             exposure='trust_mechanisms')
17
18 # Fit WITHOUT seed
19 med_results_fair = mediation_fair.fit(n_rep=1000)
20 med_results_fair.summary()
```

|                                 | Estimate  | Lower CI bound | Upper CI bound | P-value |
|---------------------------------|-----------|----------------|----------------|---------|
| <b>ACME (control)</b>           | -0.007916 | -0.037515      | 0.009853       | 0.470   |
| <b>ACME (treated)</b>           | -0.007916 | -0.037515      | 0.009853       | 0.470   |
| <b>ADE (control)</b>            | 0.226671  | 0.073496       | 0.390562       | 0.006   |
| <b>ADE (treated)</b>            | 0.226671  | 0.073496       | 0.390562       | 0.006   |
| <b>Total effect</b>             | 0.218755  | 0.064738       | 0.376815       | 0.006   |
| <b>Prop. mediated (control)</b> | -0.024911 | -0.296661      | 0.049838       | 0.476   |
| <b>Prop. mediated (treated)</b> | -0.024911 | -0.296661      | 0.049838       | 0.476   |
| <b>ACME (average)</b>           | -0.007916 | -0.037515      | 0.009853       | 0.470   |
| <b>ADE (average)</b>            | 0.226671  | 0.073496       | 0.390562       | 0.006   |
| <b>Prop. mediated (average)</b> | -0.024911 | -0.296661      | 0.049838       | 0.476   |

```
1 safety_var = "safety_overall"
2
3 med_safe_model = ols(f"{safety_var} ~ trust_mechanisms", data=df)
```

```

4 out_safe_model = ols("intention_overall ~ safety_overall + trust_mechanisms", data=df)
5
6 mediation_safe = Mediation(out_safe_model,
7                             med_safe_model,
8                             mediator=safety_var,
9                             exposure='trust_mechanisms')
10
11 med_results_safe = mediation_safe.fit(n_rep=1000)
12
13 print(med_results_safe.summary())
14

```

|                          | Estimate  | Lower CI bound | Upper CI bound | P-value |
|--------------------------|-----------|----------------|----------------|---------|
| ACME (control)           | -0.027106 | -0.070018      | 0.003793       | 0.102   |
| ACME (treated)           | -0.027106 | -0.070018      | 0.003793       | 0.102   |
| ADE (control)            | 0.242170  | 0.094590       | 0.400437       | 0.004   |
| ADE (treated)            | 0.242170  | 0.094590       | 0.400437       | 0.004   |
| Total effect             | 0.215065  | 0.064185       | 0.380135       | 0.008   |
| Prop. mediated (control) | -0.116809 | -0.675033      | 0.021198       | 0.110   |
| Prop. mediated (treated) | -0.116809 | -0.675033      | 0.021198       | 0.110   |
| ACME (average)           | -0.027106 | -0.070018      | 0.003793       | 0.102   |
| ADE (average)            | 0.242170  | 0.094590       | 0.400437       | 0.004   |
| Prop. mediated (average) | -0.116809 | -0.675033      | 0.021198       | 0.110   |

```

1 X = sm.add_constant(df[[fairness_var, safety_var, 'distrust_overall']])
2 y = df['intention_overall']
3 model_controls = sm.OLS(y, X).fit()
4 print(model_controls.summary())
5

```

```

=====
                        OLS Regression Results
=====
Dep. Variable:      intention_overall    R-squared:                0.094
Model:              OLS                 Adj. R-squared:           0.077
Method:             Least Squares       F-statistic:             5.513
Date:               Wed, 10 Dec 2025    Prob (F-statistic):      0.00125
Time:               08:17:11           Log-Likelihood:          10.490
No. Observations:   164                AIC:                   -12.98
Df Residuals:       160                BIC:                   -0.5796
Df Model:            3
Covariance Type:    nonrobust
=====

```

|                  | coef    | std err | t                 | P> t  | [0.025   | 0.975] |
|------------------|---------|---------|-------------------|-------|----------|--------|
| -----            | -----   | -----   | -----             | ----- | -----    | -----  |
| const            | 4.4371  | 0.271   | 16.383            | 0.000 | 3.902    | 4.972  |
| fairness_overall | -0.0200 | 0.046   | -0.432            | 0.666 | -0.111   | 0.071  |
| safety_overall   | -0.0739 | 0.040   | -1.836            | 0.068 | -0.153   | 0.006  |
| distrust_overall | 0.1536  | 0.041   | 3.778             | 0.000 | 0.073    | 0.234  |
| -----            | -----   | -----   | -----             | ----- | -----    | -----  |
| Omnibus:         | 65.617  |         | Durbin-Watson:    |       | 2.177    |        |
| Prob(Omnibus):   | 0.000   |         | Jarque-Bera (JB): |       | 240.976  |        |
| Skew:            | -1.519  |         | Prob(JB):         |       | 4.71e-53 |        |
| Kurtosis:        | 8.103   |         | Cond. No.         |       | 105.     |        |

```

=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

```

1 # Save descriptives and correlations to Excel
2 with pd.ExcelWriter("ENT636_analysis_output.xlsx") as writer:
3     item_desc.to_excel(writer, sheet_name="Item_Descriptives")
4     construct_desc.to_excel(writer, sheet_name="Construct_Descriptives")
5     corr_matrix.to_excel(writer, sheet_name="Correlations")
6

```

## 1. Reliability table

```

1 import pandas as pd
2
3 reliability_df = pd.DataFrame({
4     "Scale": ["Distrust overall", "Trust mechanisms", "Intention overall"],
5     "Cronbach_alpha": [alpha_distrust, alpha_trust, alpha_intention],
6     "N_items": [len(distrust_items), len(trust_items), len(intention_items)]
7 })
8
9 reliability_df

```

Scale

Cronbach\_alpha

N\_items

|   |                   |          |   |
|---|-------------------|----------|---|
| 0 | Distrust overall  | 0.635345 | 8 |
| 1 | Trust mechanisms  | 0.504909 | 5 |
| 2 | Intention overall | 0.109230 | 3 |

Next steps:

[Generate code with reliability\\_df](#)

[New interactive sheet](#)

2. Tidy regression tables (H1–H4)

```
1 import numpy as np
2
3 def tidy_ols(dv_label, model):
4     ci = model.conf_int()
5     df = pd.DataFrame({
6         "DV": dv_label,
7         "Predictor": model.params.index,
8         "b": model.params.values,
9         "SE": model.bse.values,
10        "p": model.pvalues.values,
11        "CI_low": ci[0].values,
12        "CI_high": ci[1].values,
13    })
14    df["R2"] = model.rsquared
15    df["Adj_R2"] = model.rsquared_adj
16    df["F"] = model.fvalue
17    df["F_p"] = model.f_pvalue
18    return df
19
20 reg_tables = [
21     tidy_ols("fairness_overall", model_h1),      # H1
22     tidy_ols("safety_overall", model_h2),        # H2
23     tidy_ols("intention_overall (fairness)", model_h3), # H3
24     tidy_ols("intention_overall (safety)", model_h4), # H4
25 ]
26
27 regression_df = pd.concat(reg_tables, ignore_index=True)
28 regression_df
```

|   | DV                           | Predictor        | b         | SE       | p            | CI_low    | CI_high  | R2       | Adj_R2    | F        | F_p      |
|---|------------------------------|------------------|-----------|----------|--------------|-----------|----------|----------|-----------|----------|----------|
| 0 | fairness_overall             | const            | 4.835177  | 0.673845 | 2.448311e-11 | 3.504525  | 6.165829 | 0.007726 | 0.001601  | 1.261302 | 0.263066 |
| 1 | fairness_overall             | trust_mechanisms | -0.156527 | 0.139373 | 2.630665e-01 | -0.431749 | 0.118695 | 0.007726 | 0.001601  | 1.261302 | 0.263066 |
| 2 | safety_overall               | const            | 2.089602  | 0.744247 | 5.603451e-03 | 0.619925  | 3.559278 | 0.034042 | 0.028080  | 5.709196 | 0.018026 |
| 3 | safety_overall               | trust_mechanisms | 0.367810  | 0.153934 | 1.802563e-02 | 0.063833  | 0.671786 | 0.034042 | 0.028080  | 5.709196 | 0.018026 |
| 4 | intention_overall (fairness) | const            | 4.497275  | 0.185542 | 9.171436e-56 | 4.130882  | 4.863667 | 0.004689 | -0.001455 | 0.763144 | 0.383639 |
| 5 | intention_overall (fairness) | fairness_overall | 0.039532  | 0.045253 | 3.836394e-01 | -0.049829 | 0.128893 | 0.004689 | -0.001455 | 0.763144 | 0.383639 |
| 6 | intention_overall (safety)   | const            | 4.862097  | 0.156937 | 5.706829e-70 | 4.552191  | 5.172003 | 0.010424 | 0.004316  | 1.706485 | 0.193294 |
| 7 | intention_overall (safety)   | safety_overall   | -0.052656 | 0.040309 | 1.932938e-01 | -0.132254 | 0.026942 | 0.010424 | 0.004316  | 1.706485 | 0.193294 |

Next steps:

[Generate code with regression\\_df](#)

[New interactive sheet](#)

```
1 regression_df
```

|   | DV                           | Predictor        | b         | SE       | p            | CI_low    | CI_high  | R2       | Adj_R2    | F        | F_p      |
|---|------------------------------|------------------|-----------|----------|--------------|-----------|----------|----------|-----------|----------|----------|
| 0 | fairness_overall             | const            | 4.835177  | 0.673845 | 2.448311e-11 | 3.504525  | 6.165829 | 0.007726 | 0.001601  | 1.261302 | 0.263066 |
| 1 | fairness_overall             | trust_mechanisms | -0.156527 | 0.139373 | 2.630665e-01 | -0.431749 | 0.118695 | 0.007726 | 0.001601  | 1.261302 | 0.263066 |
| 2 | safety_overall               | const            | 2.089602  | 0.744247 | 5.603451e-03 | 0.619925  | 3.559278 | 0.034042 | 0.028080  | 5.709196 | 0.018026 |
| 3 | safety_overall               | trust_mechanisms | 0.367810  | 0.153934 | 1.802563e-02 | 0.063833  | 0.671786 | 0.034042 | 0.028080  | 5.709196 | 0.018026 |
| 4 | intention_overall (fairness) | const            | 4.497275  | 0.185542 | 9.171436e-56 | 4.130882  | 4.863667 | 0.004689 | -0.001455 | 0.763144 | 0.383639 |
| 5 | intention_overall (fairness) | fairness_overall | 0.039532  | 0.045253 | 3.836394e-01 | -0.049829 | 0.128893 | 0.004689 | -0.001455 | 0.763144 | 0.383639 |
| 6 | intention_overall (safety)   | const            | 4.862097  | 0.156937 | 5.706829e-70 | 4.552191  | 5.172003 | 0.010424 | 0.004316  | 1.706485 | 0.193294 |
| 7 | intention_overall (safety)   | safety_overall   | -0.052656 | 0.040309 | 1.932938e-01 | -0.132254 | 0.026942 | 0.010424 | 0.004316  | 1.706485 | 0.193294 |

Next steps:

[Generate code with regression\\_df](#)

[New interactive sheet](#)

### 3. Export everything to one Excel file

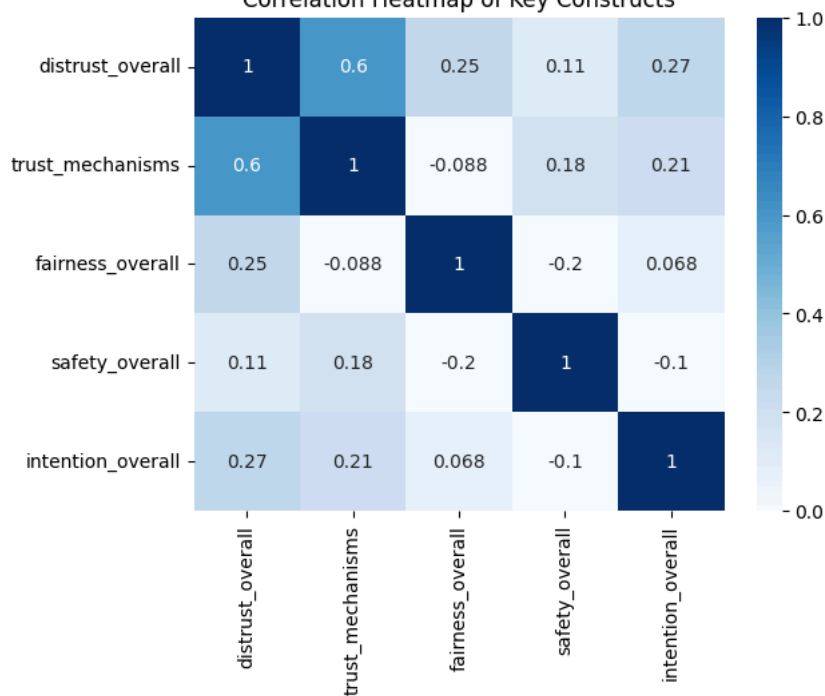
```
1 with pd.ExcelWriter("ENT636_results_tables.xlsx") as writer:
2     # Item-level descriptives
3     item_desc.to_excel(writer, sheet_name="Item_Descriptives")
4
5     # Construct-level descriptives
6     construct_desc.to_excel(writer, sheet_name="Scale_Descriptives")
7
8     # Reliability
9     reliability_df.to_excel(writer, sheet_name="Reliability", index=False)
10
11    # Correlations
12    corr_matrix.to_excel(writer, sheet_name="Correlations")
13
14    # Regressions
15    regression_df.to_excel(writer, sheet_name="Regressions", index=False)
```

```
1 def describe_model(label, model):
2     lines = []
3     lines.append(f"{label}")
4     lines.append(f"    R2 = {model.rsquared:.3f}, "
5                 f"Adj R2 = {model.rsquared_adj:.3f}, "
6                 f"F({int(model.df_model)}, {int(model.df_resid)}) = {model.fvalue:.2f}, "
7                 f"p = {model.f_pvalue:.3f}")
8     for name, coef, p in zip(model.params.index[1:], model.params.values[1:], model.pvalues.values[1:]):
9         lines.append(f"    {name}: β = {coef:.3f}, p = {p:.3f}")
10    return "\n".join(lines)
11
12 text_lines = []
13 text_lines.append(describe_model("H1: trust → fairness", model_h1))
14 text_lines.append("")
15 text_lines.append(describe_model("H2: trust → safety", model_h2))
16 text_lines.append("")
17 text_lines.append(describe_model("H3: fairness → intention", model_h3))
18 text_lines.append("")
19 text_lines.append(describe_model("H4: safety → intention", model_h4))
20
21 with open("ENT636_regression_summary.txt", "w", encoding="utf-8") as f:
22     f.write("\n\n".join(text_lines))
```

### Correlation Heatmap

```
1 import seaborn as sns
2 import matplotlib.pyplot as plt
3
4 sns.heatmap(df[corr_vars].corr(), annot=True, cmap="Blues", vmin=0.0, vmax=1.0)
5 plt.title("Correlation Heatmap of Key Constructs")
6 plt.show()
```

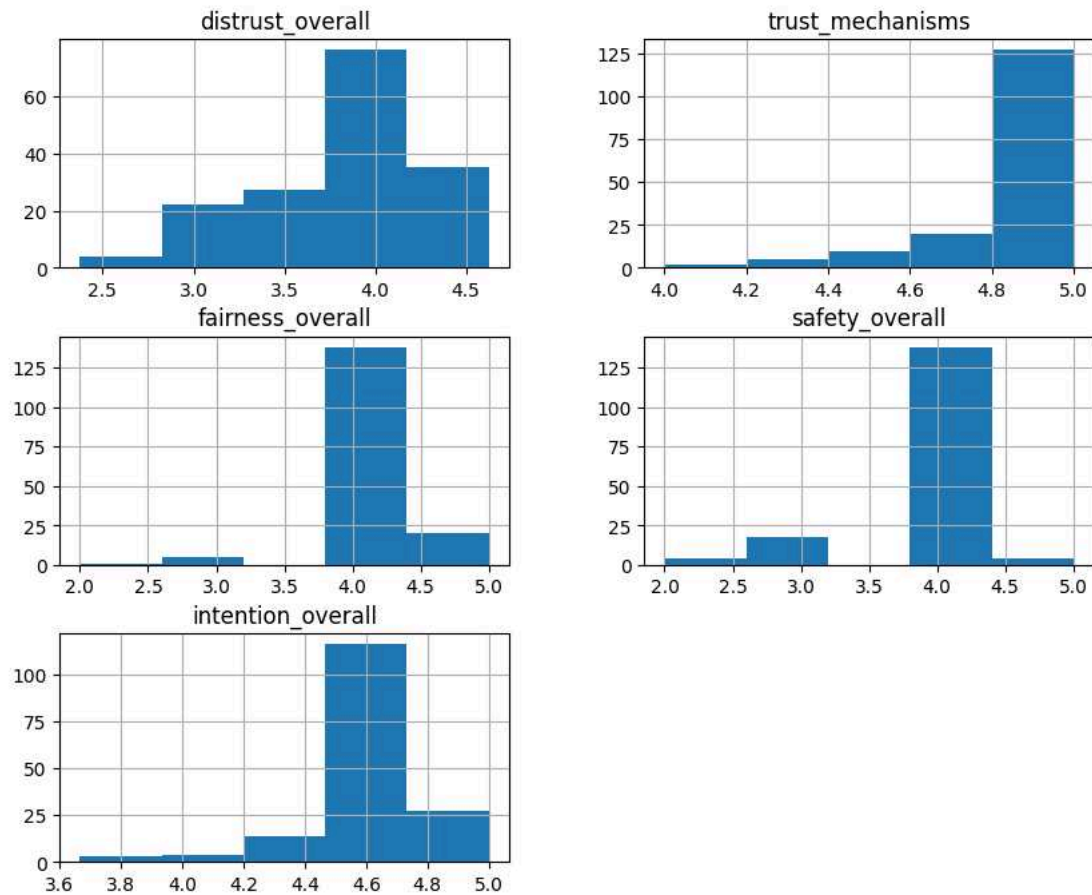
Correlation Heatmap of Key Constructs



## ✧ Distribution Plots / Histograms of Constructs

```
1 df[constructs].hist(figsize=(10,8), bins=5)
2 plt.suptitle("Distribution of Key Psychological Constructs")
3 plt.show()
```

Distribution of Key Psychological Constructs

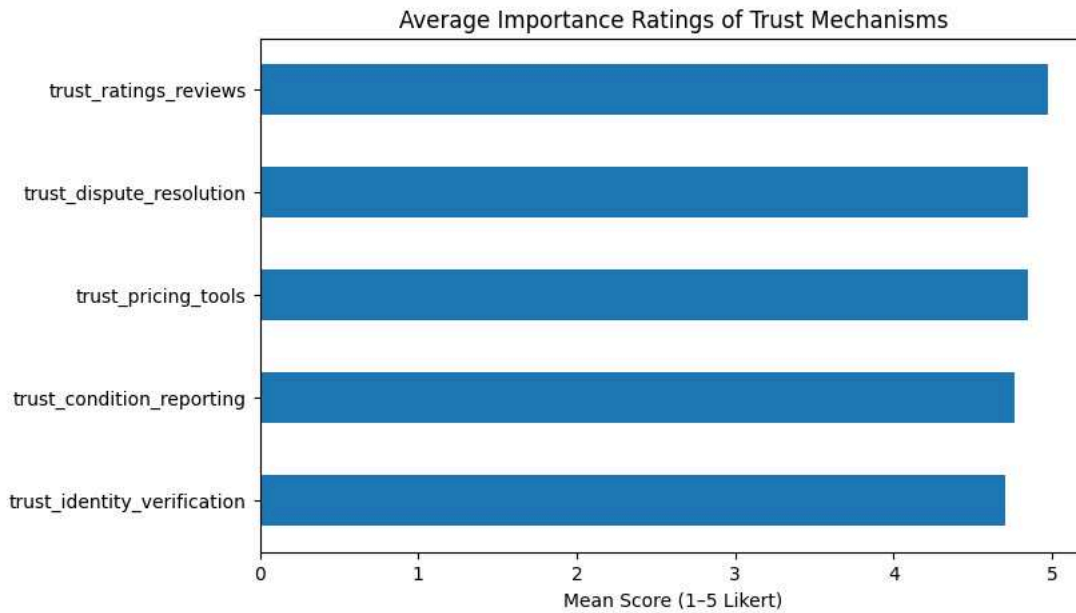


## ✧ Bar Chart Ranking Trust Mechanisms by Mean Score

```

1 trust_means = df[trust_items].mean().sort_values()
2
3 trust_means.plot(kind='barh', figsize=(8,5))
4 plt.title("Average Importance Ratings of Trust Mechanisms")
5 plt.xlabel("Mean Score (1-5 Likert)")
6 plt.show()
7

```

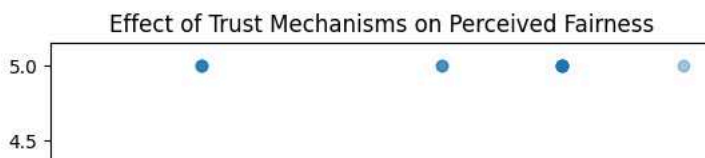


## Regression Effect Plots

```

1 import numpy as np
2 import matplotlib.pyplot as plt
3
4 X = df['trust_mechanisms']
5 y_pred = model_h1.predict(sm.add_constant(X))
6
7 plt.scatter(X, df['fairness_overall'], alpha=0.4)
8 plt.plot(X, y_pred, color="red")
9 plt.xlabel("Trust Mechanisms")
10 plt.ylabel("Fairness Perception")
11 plt.title("Effect of Trust Mechanisms on Perceived Fairness")
12 plt.show()
13

```



### 8.3 Appendix C: Quantitative Results Tables (Excel Export).

- (1) **Item-level descriptives** (count, mean, SD, min, max for each survey item)
- (2) **Scale-level descriptives** (aggregate mean and SD for each construct)
- (3) **Reliability coefficients** (Cronbach's alpha for each multi-item scale, with number of items)
- (4) **Pearson correlation matrix** for the main constructs (distrust, trust mechanisms, fairness, safety, intention)
- (5) **Regression** summary results for each hypothesis test (including estimated coefficients, standard errors, p-values,  $R^2$ , and 95% confidence intervals for H1–H4 models). These structured tables provide a quick reference to the quantitative findings discussed in the report.

| Feature                        | count | mean      | std       | min | 25% | 50% | 75% | max |
|--------------------------------|-------|-----------|-----------|-----|-----|-----|-----|-----|
| distrust_exaggerated_condition | 164   | 4.5365854 | 0.794075  | 1   | 4   | 5   | 5   | 5   |
| distrust_undisclosed_defects   | 164   | 4.2926829 | 0.8138043 | 1   | 4   | 4   | 5   | 5   |
| distrust_unfair_pricing        | 164   | 4.554878  | 0.6576874 | 1   | 4   | 5   | 5   | 5   |
| distrust_unclear_description   | 164   | 3.6829268 | 0.7410496 | 1   | 3   | 4   | 4   | 5   |
| distrust_buyers_incomplete     | 164   | 3.6402439 | 0.8500249 | 1   | 3   | 4   | 4   | 5   |
| distrust_excessive_bargaining  | 164   | 2.7195122 | 1.2991209 | 1   | 2   | 2   | 4   | 5   |
| distrust_nonserious_buyers     | 164   | 3.4573171 | 1.0173381 | 1   | 3   | 4   | 4   | 5   |
| distrust_buyer_reliability     | 164   | 3.7621951 | 0.6349997 | 2   | 4   | 4   | 4   | 5   |
| trust_identity_verification    | 164   | 4.7073171 | 0.5073159 | 2   | 4   | 5   | 5   | 5   |
| trust_ratings_reviews          | 164   | 4.9756098 | 0.1547299 | 4   | 5   | 5   | 5   | 5   |
| trust_condition_reporting      | 164   | 4.7682927 | 0.4512771 | 3   | 5   | 5   | 5   | 5   |
| trust_pricing_tools            | 164   | 4.847561  | 0.393108  | 3   | 5   | 5   | 5   | 5   |
| trust_dispute_resolution       | 164   | 4.847561  | 0.4084162 | 2   | 5   | 5   | 5   | 5   |
| fairness_overall               | 164   | 4.0792683 | 0.4142368 | 2   | 4   | 4   | 4   | 5   |
| safety_overall                 | 164   | 3.8658537 | 0.4637059 | 2   | 4   | 4   | 4   | 5   |
| intention_complete_transaction | 164   | 4.1463415 | 0.5565439 | 2   | 4   | 4   | 4   | 5   |
| intention_use_more             | 164   | 4.8841463 | 0.3210296 | 4   | 5   | 5   | 5   | 5   |
| intention_influenced_by_trust  | 164   | 4.945122  | 0.2538791 | 3   | 5   | 5   | 5   | 5   |

Table-1: Item\_Descriptives

| Feature           | count | mean        | std         | min         | 25%         | 50%         | 75%         | max   |
|-------------------|-------|-------------|-------------|-------------|-------------|-------------|-------------|-------|
| distrust_overall  | 164   | 3.830792683 | 0.464156977 | 2.375       | 3.5         | 4           | 4.125       | 4.625 |
| trust_mechanisms  | 164   | 4.829268293 | 0.232610053 | 4           | 4.8         | 5           | 5           | 5     |
| fairness_overall  | 164   | 4.079268293 | 0.414236767 | 2           | 4           | 4           | 4           | 5     |
| safety_overall    | 164   | 3.865853659 | 0.463705934 | 2           | 4           | 4           | 4           | 5     |
| intention_overall | 164   | 4.658536585 | 0.239151019 | 3.666666667 | 4.666666667 | 4.666666667 | 4.666666667 | 5     |

Table-2: Scale\_Descriptives

| Scale             | Cronbach_alpha | N_items |
|-------------------|----------------|---------|
| Distrust overall  | 0.635345078    | 8       |
| Trust mechanisms  | 0.504908739    | 5       |
| Intention overall | 0.109229651    | 3       |

Table-3: Reliability

| Feature           | distrust_overall | trust_mechanisms | fairness_overall | safety_overall | intention_overall |
|-------------------|------------------|------------------|------------------|----------------|-------------------|
| distrust_overall  | 1                | 0.598747971      | 0.249669961      | 0.114797871    | 0.273083294       |
| trust_mechanisms  | 0.598747971      | 1                | -0.087895744     | 0.184505385    | 0.210166831       |
| fairness_overall  | 0.249669961      | -0.087895744     | 1                | -0.199813401   | 0.068473939       |
| safety_overall    | 0.114797871      | 0.184505385      | -0.199813401     | 1              | -0.102098239      |
| intention_overall | 0.273083294      | 0.210166831      | 0.068473939      | -0.102098239   | 1                 |

Table-4: Correlations

| DV                           | Predictor        | b            | SE          | p           | CI_low       | CI_high     | R2          | Adj_R2       | F           | F_p         |
|------------------------------|------------------|--------------|-------------|-------------|--------------|-------------|-------------|--------------|-------------|-------------|
| fairness_overall             | const            | 4.835176991  | 0.673845    | 2.44831E-11 | 3.504524632  | 6.16582935  | 0.007725662 | 0.001600512  | 1.261301599 | 0.263066478 |
| fairness_overall             | trust_mechanisms | -0.156526549 | 0.139372964 | 0.263066478 | -0.431748541 | 0.118695444 | 0.007725662 | 0.001600512  | 1.261301599 | 0.263066478 |
| safety_overall               | const            | 2.08960177   | 0.744247199 | 0.005603451 | 0.619925078  | 3.559278462 | 0.034042237 | 0.028079535  | 5.709196219 | 0.018025629 |
| safety_overall               | trust_mechanisms | 0.367809735  | 0.153934418 | 0.018025629 | 0.063833009  | 0.67178646  | 0.034042237 | 0.028079535  | 5.709196219 | 0.018025629 |
| intention_overall (fairness) | const            | 4.497274907  | 0.185541907 | 9.17144E-56 | 4.130882375  | 4.86366744  | 0.00468868  | -0.001455217 | 0.763144356 | 0.383639399 |
| intention_overall (fairness) | fairness_overall | 0.039532011  | 0.04525281  | 0.383639399 | -0.049829428 | 0.12889345  | 0.00468868  | -0.001455217 | 0.763144356 | 0.383639399 |
| intention_overall (safety)   | const            | 4.862096961  | 0.156936976 | 5.70683E-70 | 4.552191038  | 5.172002885 | 0.01042405  | 0.004315557  | 1.706484651 | 0.19329376  |
| intention_overall (safety)   | safety_overall   | -0.052655996 | 0.0403085   | 0.19329376  | -0.132253828 | 0.026941836 | 0.01042405  | 0.004315557  | 1.706484651 | 0.19329376  |

Table-5: Regressions

## **8.4 Appendix D: Summary of Regression Outputs and Additional Analysis.**

- This section includes any additional summary tables or documentation of analyses not fully detailed in the main text. For instance, if any exploratory regressions or subgroup analyses were conducted (such as examining the regression models with demographic control variables, or splitting the sample by primary role), their results can be tabulated here. Additionally, a concise table highlighting the hypothesis outcomes (supported vs. not supported) may be provided for clarity. This appendix ensures that all statistical results are accessible for verification and that the decision logic for conclusions is transparent.

H1: trust → fairness

$R^2 = 0.008$ , Adj  $R^2 = 0.002$ ,  $F(1, 162) = 1.26$ ,  $p = 0.263$

trust\_mechanisms:  $\beta = -0.157$ ,  $p = 0.263$

H2: trust → safety

$R^2 = 0.034$ , Adj  $R^2 = 0.028$ ,  $F(1, 162) = 5.71$ ,  $p = 0.018$

trust\_mechanisms:  $\beta = 0.368$ ,  $p = 0.018$

H3: fairness → intention

$R^2 = 0.005$ , Adj  $R^2 = -0.001$ ,  $F(1, 162) = 0.76$ ,  $p = 0.384$

fairness\_overall:  $\beta = 0.040$ ,  $p = 0.384$

H4: safety → intention

$R^2 = 0.010$ , Adj  $R^2 = 0.004$ ,  $F(1, 162) = 1.71$ ,  $p = 0.193$

safety\_overall:  $\beta = -0.053$ ,  $p = 0.193$