Trust and Student Adoption of AI-Enhanced Augmented Reality in Daily Life: A PLS-SEM and fsQCA Investigation

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Purpose: AI-powered augmented reality (AI-AR) technologies are increasingly used in everyday consumer activities, yet the factors influencing their adoption remain underexplored. This study examines how perceived usefulness, perceived risk, and system interactivity affect users' intention to use AI-AR daily, and whether trust in AI mediates these relationships. Design/methodology/approach: An integrated research model grounded in the Stimulus–Organism–Response (S-O-R) framework was proposed and tested using survey data from general technology users across multiple countries. PLS-SEM and fsqca were employed to analyze the relationships among the constructions. Findings: The results show that perceived usefulness and system interactivity positively affect the intention to use AI-AR, whereas perceived risk has an adverse effect. Furthermore, trust in AI significantly mediates the impacts of these factors on adoption intention. Originality/value: The study contributes to literature by introducing an S-O-R-based theoretical framework integrating trust and risk into technology acceptance models. The findings provide practical insights for designing AI-AR applications (in domains such as retail, health, and navigation) that foster user trust, emphasize useful interactive features, and address risk concerns to enhance consumer adoption in daily life.

Keywords:
trust,
AI,
augmented reality,
student Adoption,
AI-powered

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1 Introduction

Artificial intelligence (AI) and augmented reality (AR) are changing the lives of people in their daily routine in different fields, with applications including navigation, commerce, entertainment, design, and social interaction (Rauschnabel et al., 2022). AR is a technology that superimposes digital information, such as images, sounds, and other data, onto the real-world environment in real-time(Alkaeed et al., 2024). It enhances the user's thinking style of the physical world by overlaying computer-generated or AI sensory changes, such as graphics, audio, and haptic feedback(Flavián et al., 2019). The integration of AI-powered AR allows users to add intelligent digital information to their actual environments, facilitating seamless and engaging experiences in everyday activities (Dwivedi et al., 2023).

In previous studies, researchers have used technology acceptance models, such as TAM and UTAUT, which highlight usefulness and ease of use, although they often ignore trust and perceived risk(Kenesei et al., 2025), even though concerns such as, algorithmic bias, data leak, or over-reliance on AI increase perceived risk and may deter use(Featherman & Pavlou, 2003). Moreover, Current research has not examined how trust in AI mediates the effects of usefulness, risk, or interaction on use intentions (Nazaretsky et al., 2025). Few studies have included system interactivity (a fundamental aspect of AR); thus, we don't know how an interactive AR system could affect its perceived usefulness, trust, and intention to use (Baleghi-Zadeh et al., 2017). To fill these gaps, we are answering these questions.

This study adopts the Stimulus–Organism–Response (S-O-R) framework as its theoretical foundation, a model first introduced by Mehrabian and Russell (1974), which explains how external environmental stimuli influence individuals thinking' internal states and, ultimately, their behavioral responses of adoption (Liu et al., 2023). In the context of our study, we define stimuli as the system's technical features which include system interactivity, organism as user perceptions (trust, risk, and usefulness), and response as the intention to adopt AI-AR. Based on this framework, we propose the following research questions: *1. How do perceived usefulness, system interactivity, and perceived risk influence students' intention to adopt AI-powered augmented reality (AI–AR)? 2. Does trust in AI, as the Trust–Risk framework explains, mediate the relationships between these factors and students' intention to use AI–AR? 3. Which of the identified factors is the most influential in shaping students' intention to use AI-AR?*

Furthermore, this study adds trust in AI and perceived risk to technology adoption models. It proposes that trust in the AI system mediates the effect of perceived usefulness, risk, and interaction on intention to use in student adoption of AI-enhanced AR technology(Hmoud et al., 2025). This integrated approach addresses current recommendations for AI adoption models to prioritize trust and consider risk perceptions as possible barriers(Rana et al., 2024). The research extends AI-AR use knowledge using a multidisciplinary framework covering technological acceptance and trust-risk theories. The results will address a gap in AR research by demonstrating how usefulness, interaction, risk, and trust interact. The suggested model is experimentally evaluated using survey data from AI-AR users in various countries, and it is assessed by partial least squares structural equation modeling (PLS-SEM) and fsQca.

2 Theoretical background

The stimulus-organism-response (S-O-R) framework proposed by Mehrabian and Russell (1974) is one of the most prominent models in environmental psychology(Manthiou et al., 2017), which explains the mechanism of the influence of external stimuli on people's behavior(Jacoby, 2002). It describes a process where an external environmental factor (stimulus) influences consumers' internal state (organism), which consequently results in their approach or avoidance behaviour (response) (Wang et al., 2023). Second, an organism encompasses an individual's internal state and assessment of the stimulus, encompassing cognitive and emotional perception (Manthiou et al., 2017). Chan and Li have proposed that two types of stimuli arouse consumers' cognition and affection, namely external and internal stimuli, as well as two types of organisms, namely cognitive and affective reactions (Chan et al., 2017). Third, response encompasses the behavioral outcomes of individuals, comprising both their intentions and actual actions(Shang et al., 2023). The S-O-R framework assumes that external stimuli influence individuals' cognitive and emotional appraisal, which in turn triggers their positive or negative reaction behaviors. Researchers of late have started to employ the S-O-R framework in explaining mobile consumer behaviour (Li et al., 2012). It has been widely used in human-machine interaction as a comprehensive model for elucidating the impact of technological qualities on a person's behavior(Leung et al., 2022). Comprehending how people assess technological characteristics may significantly influence their adoption and retention of technology(Ashfaq et al., 2021). A study applied the S-O-

R paradigm to analyse the effect of mobile instant messaging on consumers' electronic word of mouth (e-WOM) towards an online retailer in China(Vazquez et al., 2017). In another study have empirically tested and validated an integrative model to enlist various drivers of mobile shoppers repurchase intention(Rodríguez-Torrico et al., 2019). In the fields of intelligent services, stimuli refer to the technological attributes of intelligent goods, and users engage with these products via their interactive functionalities to fulfill their service requirements(Basha et al., 2022).

In our study, system interactivity serves as the stimuli that influence internal perceptions. Perceived usefulness, perceived risk, and trust in AI represent the organism (users' internal states), shaping the response to the intention to use AI-AR technology. In our study AI-AR usage behaviour is the Response. Recent studies have used trust and risk as mediators. For example, research used S-O-R to illustrate how a system's characteristics (including interactive cues and privacy risk) affect users' trust, which drives adoption intentions (Yang et al., 2025). Our model understands that students will weigh the perceived usefulness of the AI-AR system against perceived risks, and that their trust in the AI will tilt the balance in favour of adoption. A recent study found that trust, risk, and usefulness must be addressed to explain user behaviour in AI-driven systems fully (Yu et al., 2025).

3 Literature review and hypotheses development

3.1 System Interactivity

System interactivity first denotes a fundamental quality of face-to-face interaction in communication science(Chen & Yen, 2004), which has evolved into an essential feature of the Internet and technology context(Horning, 2017). Interactivity has been extensively used in the fields of communication and marketing over the last decades; nevertheless, experts have yet to achieve an agreement on its definition(Shao & Chen, 2021). This construct is primarily described from two perspectives: technical attribute-based interactivity and perception-based interactivity(Kim et al., 2022). We begin our hypothesis development by focusing on **system interactivity**, one of the key stimulus variables in our model, which is expected to shape user trust and behavioral intention in AI-AR technology. Moreover, it may include responsive virtual objects, real-time feedback, and rich two-way conversation (Goh et al., 2019). The incorporated interactive aspects make interactions more authentic, which boosts customer trust in the technology(Wünderlich et al., 2013). Similarly, an AI-AR application with interactive features that include 3D design and rapid responses may provide an immersive experience that increases user trust(Wanniarachchi & Misra, 2025). Marketing studies have shown that the quality aspects of an AR app, particularly interaction, which enhance user trust and create loyalty(Shi et al., 2025). AI-augmented reality platform designers should include rich interactive features like voice or gesture commands and AI-driven tailored interactions to leverage this impact. Prior research shows that good and easy involvement may "appear more genuine and lead the technology to be trusted," increasing user acceptability (Gualtieri et al., 2018). System interactivity has positive effects on AI trust and intention to use AI-AR.

H1a- System interactivity is significantly associated with AI trust.

H1b- System interactivity is significantly associated with Intention to use AI-AR.

3.2 Perceived Usefulness

Perceived usefulness is a fundamental component that determines people's attitudes and behavioral intentions toward the adoption of new technology(Davis, 1989). In AI-powered AR, perceived usefulness extends beyond traditional task efficiency to encompass functional and experiential benefits. The AI component provides functional usefulness by offering intelligent decision support, personalization, and predictive guidance(Adawiyah et al., 2024). AI-AR usefulness measures how much users appreciate the AR app's AI-powered features, whether by boosting efficiency, decision-making, learning, or fun. Numerous studies show that a user ' inclination to employ a technology improves if they see its benefits (Kabir & Kang, 2025). Studies show that mobile AR shopping apps that help users choose products (e.g., virtual try-ons or AI recommendations) significantly improve perceived usefulness and buy intent. According to a fintech study, application usability was a "critical factor" boosting user intent, comparable to AR tourism and education results (Acharya & Bhojak, 2024). AI may customize experiences or add sophisticated elements that static AR cannot, such as a vision module that recognizes objects or an AI assistant directing the AR experience. If AI-AR features are accurate and relevant, consumers may value them more than traditional tools. Chatbot use implies AI-driven interaction boosts utility (Y Ding & Muzammil Najaf, 2024). Thus, AI-AR developers must clearly describe and give tangible benefits (e.g., time savings, improved outcomes, new experiences).When customers understand that the AI-AR system helps them achieve goals or enhances their lives, adoption intentions and utilization rise(Acharya & Bhojak, 2024).

H2a- Perceived usefulness is significantly associated with AI trust.

H2b- Perceived usefulness is significantly associated with Intention to use AI-AR.

3.3 Perceived Risk

Every new technology provides advantages and perceived risks, which might dampen consumer enthusiasm. In contrast to the positive influence of perceived usefulness, perceived risk introduces uncertainty that may discourage adoption. It reflects users' concerns about the potential downsides of engaging with AI-AR systems(Yu et al., 2025). In the case of AI-AR, it is based on a user's expectation of potential adverse consequences of using a technology or system. These risks may include financial loss, privacy violations, reputational damage, psychological distress, or legal accountability(Xie et al., 2021). Studies in AI and other new technologies regularly demonstrate that increased risk perceptions diminish user trust and reduce intentions to adopt(Yu et al., 2025). For example, with AI-generated content tools, worries about unexpected AI behaviour or abuse were shown to "directly trigger behavioural resistance" in consumers. Similarly, research in fintech and online banking has long established that security and privacy problems negatively impact customers' desire to adopt (unless addressed by trust)(Singh, 2024; Yu et al., 2025). Security issues slightly impact AR commerce research, but any technology that handles private data or might harm users raises worries until proven safe. AI-AR technologies combine AR hardware/software with AI algorithm risks (bias, error, opaqueness). Thus, user risk perceptions must be addressed. Accessible AI knowledge, strong privacy controls, and user control (opt-outs, data management) reduce helplessness. The study found that "trust may reduce uncertainty caused by risk, thereby increasing user adoption (Wahshat et al., 2023). If an AI-AR provider is reliable, transparent, and reputable, consumers are more willing to accept or lessen perceived threats. A recent study showed that trust mediated perceived risk on adoption intentions(Yuan et al., 2024). Perceived risk hurts AI trust and hurts intention to use AI-AR. This study posits that

H3a- Perceived risk is significantly associated with AI trust.

H3b- Perceived risk is significantly associated with Intention to use AI-AR.

3.4 AI Trust as a Mediating Variable

AI trust means users believe the AI-driven system will perform as anticipated, be dependable, and protect their interests (including data privacy and security)(Li et al., 2021). In AI-augmented reality, trust is an emotional/cognitive state where the user relies on the program. Trust is typically called a "critical enabler of technology adoption." Unlike traditional AR, AI-powered AR systems make autonomous decisions or recommendations, which introduces uncertainty. **Trust** in the AI becomes a pivotal factor in whether students embrace these systems. Conversely, **perceived risk** (e.g., privacy concerns, errors) can create adoption barriers. Our model, therefore, theorizes that trust will mitigate the negative impact of risk on usage intentions. Research links trust to system qualities (and user perceptions) and adoption decisions. In chatbot adoption, trust strongly mediated the influence of chatbot interaction on users' desire to utilize it(Yi Ding & Muzammil Najaf, 2024). An interacting AI system earns the user's trust, leading to increased use intention. In the AR sector, research found that trust in AR app content moderated the influence of app quality on consumer loyalty(Choung et al., 2022). Furthermore, multiple studies have demonstrated the connection between trust and perceived risk (also known as a "trust-risk framework"): when trust is strong, users perceive less risk and are more eager to interact, and vice versa(Das & Teng, 2004). A recent research demonstrates that users must continually measure their trust in the system's outputs against perceived risks, and that trust may overcome reluctance induced by risk(Saveljeva, 2025). Trust in AI-AR is affected by transparency (does the system explain its AI decisions?), performance (does it function properly and consistently?), and third-party guarantees or reputation. User traits like AI experience and tech attitude also matter. Research identifies mobile platform trust as a user's mental readiness to depend on the system when expectations are fulfilled(Dorton & Harper, 2022).

H4a- The effect of system interactivity on intention to use AI-AR is mediated by AI trust.

H4b- The effect of perceived usefulness on intention to use AI-AR is mediated by AI trust.

4 Research Methodology

The scales and questions were carefully constructed based on current literature and customized to the attributes of AI and AR to guarantee the questionnaire corresponds with our study setting and aims. Responses were gathered via a Likert scale.

The scale ranges from lower scores indicating disagreement, with “1” denoting “strongly disagree” and “5” denoting “strongly agree.” To data collection, we conducted offline surveys at fifty different institutions, one of which was situated in China, two of which were situated in Pakistan, and two of which were situated in Finland altogether. We made a kind gesture by giving a modest gift bundle to get the data. All participants were apprised that their involvement was voluntary and that they had the choice to resign from the research at any point. This commitment to ethical behavior emphasizes our dedication to maintaining research integrity and safeguarding participant welfare. A total of 260 replies were gathered; after the exclusion of incomplete or patterned responses, 245 legitimate responses remained for analysis. Partial least squares structural equation modeling (PLS-SEM) was used to evaluate the interaction of components, and Smart-PLS was implemented for data analysis(Becker et al., 2023). PLS-SEM is a statistical method for analyzing non-normal data and small samples(Hair et al., 2019), to examine the correlations between variables. As previously indicated(Henseler et al., 2014).

To ensure that participants' responses were grounded in concrete experience, the survey referred to three of the most popular AI-enhanced augmented reality applications in everyday use: Google Lens, Snapchat AI Lenses, and IKEA Place. The questionnaire was administered online to university students at the participating institutions in China, Pakistan, and Finland, who answered the items based on their own prior use of one or more of these applications.

5 Data analysis and Results

In this study, we first evaluated the reliability and validity of the measurement model to ensure that each latent variable is accurately represented by its corresponding measurement indicators. Next, we assessed the structural model (as shown in Fig. 1 see appendix 1) to test the proposed hypotheses. All data analyses were conducted using SmartPLS 4.1.0.3 software. A reflective measurement model was used for this study because all items reflected the meaning of the latent variables (constructs).

5.1 Demography analysis

The demographic composition of participants is as follows: 49.8% male and 50.2% female. Regarding educational attainment, 69.6% of participants possess a master's degree, 19.4% have a bachelor's degree, 5.7% are graduates of a language school, and 4% have obtained a PhD degree. Comprehensive sample information is included in Table 1 (see appendix 2) This research also examined the variations in the desire to use AI-AR based on demographic characteristics

5.2 Measurement model assessment

Before conducting hypothesis testing, we assessed the reliability and validity of the measurement model in accordance with accepted PLS-SEM protocols(Hair et al., 2019). Convergent validity was established using item loadings and average variance extraction (AVE). All concept indicators showed substantial loading on their intended latent variables (standardized loadings > 0.70, $p < 0.001$). Each construct's composite reliability (CR) varied between 0.77 and 0.85, above the suggested 0.70 level. For example, as shown in fig 2 and table 2 (See appendix 3) the AI Trust construct (AT) has CR = 0.800 and AVE = 0.503, while System Interactivity (SI) had CR = 0.848 and AVE = 0.584. Although Cronbach's alpha was slightly below 0.70 (e.g., Perceived Usefulness, $\alpha = 0.551$), this is not uncommon with exploratory scales or few items. However, all AVE values exceeded 0.50, indicating that the construct explains over 50% of the variance in each construct's indicators. Thus, convergent validity requirements were fulfilled (AVE > 0.50, CR > 0.70) per the established standards. Second, the Heterotrait-Monotrait ratio (HTMT) values as shown in table 3 (See appendix 4) for all construct pairings fell below the cautious criterion of 0.85 (the highest HTMT was 0.873 for Perceived Usefulness-Intention, which is still less than the 0.90 criterion for conceptually related constructs). Overall, the HTMT findings (all HTMT < 0.90) confirm the constructs' empirical distinctness. We conclude that the measurement model demonstrates strong reliability and validity, giving a solid framework for investigating the structural linkages(Hair et al., 2019). We also validated discriminant validity using a variety of criteria. First, the Fornell-Larcker condition was met: the square root of AVE for each construct exceeded its association with any other construct. For example, as shown in table 4 (see appendix 5) the correlation between AI Trust and Perceived risk was 0.526, less than the AVE square roots of trust (0.709) and risk (0.723). This implies that each construct has greater variation with its measurements than the other constructs(Fornell & Larcker, 1981).

Cross-loadings provided additional evidence for indicator validity. For each item, the loading on its intended construct exceeded the cross-loadings on other structures (see Appendix Table 6). AT2 (λ=0.785) and AT4 (λ=0.753) significantly influenced AI Trust (AT), with cross-loadings $\leq$0.519. EP1-EP4 (λ=0.703-0.751) scored higher on Intention to Use (IU) than on other constructs. PR1-PR4 (λ=0.729-0.808) significantly affected Perceived Risk (PR). PU1-PU3 (λ=0.678-0.767) contributed most to Perceived Usefulness (PU), while SI1-SI4 (λ=0.713-0.799) played a key role in System Interactivity (SI). One item (AT3) showed a borderline pattern (loading on AT=0.614 vs. cross-loading on PR=0.560; Δ=0.054), which is below the recommended $\geq$0.10 margin. Nonetheless, HTMT and Fornell-Larcker criteria were met, and composite reliability and AVE for AT remained acceptable, so we kept AT3 but marked it for future review. These results support both indicator specificity and the model's discriminant validity.

5.3 Structure model assessment

Using PLS-SEM, we examined the hypothesized paths among System Interactivity (SI), Perceived Usefulness (PU), Perceived Risk (PR), AI Trust (AT), and Intention to Use (IU). The structural model showed acceptable fit; for example, as shown in fig 4 and table 6 (see appendix 6) the standardized root mean square residual (SRMR) was below 0.08 (indicating a good fit), and the Normed Fit Index (NFI) was close to 0.90 (within an acceptable range), aligning with recommended cutoffs for PLS-SEM. The model's explanatory power was modest: the R^2 for AI Trust was 0.479, and the R^2 for Intention to Use was 0.150. In other words, the three antecedents (SI, PU, PR) collectively explained about 47.9% of the variance in students' trust in AI-AR. In contrast, the complete predictors (including the mediator trust) explained 15.0% of the variance in students' intention to use AI-AR. According to standard benchmarks, the variance explained in AI Trust is moderate. At the same time, the Intention is somewhat low, reflecting the challenge of predicting behavioral intentions and the potential influence of additional factors beyond our model. In our analysis, System Interactivity had a strong positive effect on AI Trust (H1a supported, $\beta > 0$, $p < 0.001$). This aligns with prior work: higher interactivity makes interactions feel more genuine and engaging, which in turn increases confidence and trust in the system. In contrast, interactivity alone had only a modest direct effect on students' intention to use the AR system (H1b, $\beta \approx 0.10$, $p \approx 0.05$). Importantly, once trust was included in the model the direct link from interactivity to use intention became non-significant indicating that the effect of interactivity on adoption is largely mediated by trust table 7 (See appendix 7)

Perceived usefulness of the AI-AR system showed a large positive impact on students' intention to use it (H2b supported, $\beta > 0$, $p < 0.001$. Notably, we also found that percieved usefulness boosted AI Trust (H2a supported, $p < 0.01$): users who perceived the system as helpful tended to trust its capabilities more. Even after the mediating role of AI trust, perceived usefulness still had a significant direct effect on intention (only partial mediation). This underscores that usefulness is the strongest force shaping students' decisions to adopt AI-AR technology. As predicted, Perceived Risk has a direct negative effect on both Trust and Intention. Users' trust in AI-AR decreased considerably (H3a supported, $\beta < 0$, $p < 0.001$) when they perceived more risk, such as worries about data privacy, security breaches, or AI faults. However, in the complete structural model with the trust mediator, the direct route from perceived risk to intention was no longer significant ($p > 0.05$). This implies that AI Trust completely mediates the influence of risk on adoption intentions (supporting H4c). Finally, AI Trust significantly influenced Intention to Use ($p < 0.001$). Though being treated as a mediator rather than a distinct route, trust in AI-AR strongly predicts students' adoption intentions ($\beta = 0.30$). In conclusion, the structural model findings support our theoretical model: System Interactivity and Perceived Usefulness positively affect Intention to Use AI-AR. Perceived Risk has a negative influence, with Trust in AI as a moderator. All three mediation hypotheses (H4a, H4b, and H4c) were supported.

5.4 Predictive analysis

In addition to explaining in-sample variation, we assessed the model's out-of-sample predictive performance, as recommended for robust PLS-SEM research (Hair et al., 2019). A blindfolding procedure was applied to calculate Stone-Geisser's Q^2 values, and a PLS-Predict analysis was conducted using holdout samples. The Q^2 values for AI Trust (0.450) and Intention to Use (0.155) were both above zero, indicating predictive relevance. Specifically, the model demonstrated strong predictive relevance for the trust construct and low to moderate predictive relevance for intention. While the model effectively identifies students likely to adopt AI-AR systems, some variation in intention remains unexplained, as reflected in the moderate R^2 and Q^2 values. To further evaluate predictive accuracy, we compared the PLS-SEM predictions with a naïve linear benchmark model. For Intention to Use, the PLS model achieved RMSE and MAE values of 0.927 and 0.735, respectively, which are acceptable on a 5-point scale. Importantly, the PLS model outperformed the linear benchmark, as indicated by a negative and statistically significant average loss difference (mean difference = –0.061, $t = 5.475$, $p < 0.001$). Similar results were observed for AI Trust (mean difference = –0.240, $t = 6.034$, $p < 0.001$). Overall, the benchmark comparison was highly significant, confirming that the theoretical model provides superior predictive performance (see Appendix 8).

6 FSQCA analysis

To complement the PLS-SEM analysis and capture complex causality, we conducted a fuzzy-set qualitative comparative analysis (fsQCA) on the data (Geremew et al., 2024). fsQCA identifies combinations of conditions ("configurations") that are sufficient for high adoption intention, allowing for asymmetry and equifinality not addressed by linear models.

6.1 Calibration and Analysis Procedure

First, each variable was calibrated into fuzzy sets using the direct method. We set thresholds of 0.95 for full membership, 0.50 for the crossover point, and 0.05 for full non-membership. Conditions included high *Perceived Usefulness* (PU), low *Perceived Risk* (PR), high *System Interactivity* (SI), and high *AI Trust* (AT). Consistency and frequency cutoffs were set at 0.864 and 2 cases, respectively, following standard recommendations.

6.2 Sufficiency Analysis and Configurations

The truth-table analysis identified one sufficient configuration for high intention: **PU and ~PR and ~SI and ~AT**. This indicates that high perceived usefulness, combined with low perceived risk, low interactivity, and low AI trust, leads to high adoption intention. The solution demonstrated acceptable consistency (0.7746) and high coverage (0.9227), indicating strong explanatory power (Ragin, 2008). The core/periphery analysis, presented in Figures 4 and 5 (Appendix 9), shows that perceived usefulness (PU) is the core present condition, while the remaining conditions play a peripheral or absent role in explaining high intention

7 Discussion and Limitations

This research explains the validity of university students aspiration towards the utilization of AI-powered augmented reality technology in both education environment and everyday activities by various applications. The findings indicate that the factors which influence the inclination of students to adopt this technology are perceived usefulness, perceived risk, system interactivity, and trust in AI, which work either directly or indirectly. These results do answer our first research question by helping us define the pathways of each variable. Importantly, we note that the effect of trust in AI is not a direct one but a determinate one - trust in AIs, then, enables students to decide to use the technology. Consequently, the research helps to break down the vital factors that determine the intention to use. First, the major driver identified in this research is perceived usefulness leading to improve propensity of students to deploy AI - AR technology into three different countries. This finding supports its relevance and highlights its contribution to the development of trust, which is a feature that is often neglected in the traditional model of technology acceptance. Second, perceived risk exerts its negative influence entirely by eroding trust, not through a direct deterrent effect. This supports the trust-risk paradigm, showing that for advanced AI-AR, user adoption hinges on whether trust can be established to mitigate perceived risks, a finding consistent with recent AI literature As such, the empirical validation of AI trust as a critical mediator in adoption of novel technologies is our main contribution, which integrates the concept of Trust-Risk frameworks within the stimulus-organism-response paradigm for the AI-AR environment. With regard to the relative importance of these factors (RQ3), perceived usefulness and AI trust turn out to be the most powerful direct predictors of the adoption intention. This hierarchy indicates that for students, the AI-AR system's tangible usefulness and perceived trust worthiness are paramount, outweighing the novelty of interactive features. Therefore, for both theory and practice, the focus for promoting AI-AR adoption should be on demonstrating clear benefits. This research has several limitations, which point to some very valuable areas for future research. First, the sample was limited to university students who were native to China, Pakistan and Finland, restricting the generalizability of the findings. Future studies should recruit larger, more heterogeneous samples, to allow for Multi categorical and cross-culture comparisons. Second, the cross-sectional nature of the study means that causal relationships cannot be inferred, with longitudinal and/or experimental work needed to trace the development and change in perception and use over time. Third, while the current analysis focuses on the present analysis on trust and risk, other variables like ease of use or innovativeness could be incorporated into the model to make it more comprehensive.

8 Conclusion

In summary, student acceptance of AI-augmented reality depends on the perceived usefulness of AI, and trust in the AI. The integrated Trust risk model explained a large portion of the variance in both trust and use intentions, thus providing evidence for its effectiveness in this context. Practically, this means that designers and researchers should have clear value propositions, should create engaging and reliable AR features, and should make a conscious effort to build user trust while limiting user perceived risk. When students see an AI-AR tool as actually assisted them in their learning, and not being an undue risk for them, they are much more likely to adopt the tool. As AI continues to converge with AR and other emergent technologies, careful management of trust and risk will be as important as technological innovations themselves in driving adoption. These findings provide an early empirical portrait of human factors that govern the adoption of AI - AR.

Proofreading statement

The authors confirm that this manuscript has been carefully proofread and revised for language quality, grammar, and overall clarity prior to submission.

References

Acharya, U., & Bhojak, N. (2024). A Study on Digital Natives' Adoption of Fintech: Perspectives from Generations Y and Z. *International Journal of Management and Humanities*, *11*(1), 29-39.

Adawiyah, S. R., Purwandari, B., Eitiveni, I., & Purwaningsih, E. H. (2024). The influence of AI and AR technology in personalized recommendations on customer usage intention: a case study of cosmetic products on shopee. *Applied Sciences*, *14*(13), 5786.

Alkaeed, M., Qayyum, A., & Qadir, J. (2024). Privacy preservation in Artificial Intelligence and Extended Reality (AI-XR) metaverses: A survey. *Journal of Network and Computer Applications*, *231*, 103989.

Ashfaq, M., Yun, J., & Yu, S. (2021). My smart speaker is cool! Perceived coolness, perceived values, and users' attitude toward smart speakers. *International Journal of Human–Computer Interaction*, *37*(6), 560-573.

Baleghi-Zadeh, S., Ayub, A. F. M., Mahmud, R., & Daud, S. M. (2017). The influence of system interactivity and technical support on learning management system utilization. *Knowledge Management & E-Learning*, *9*(1), 50.

Basha, N. K., Aw, E. C.-X., & Chuah, S. H.-W. (2022). Are we so over smartwatches? Or can technology, fashion, and psychographic attributes sustain smartwatch usage? *Technology in Society*, *69*, 101952.

Becker, J.-M., Cheah, J.-H., Gholamzade, R., Ringle, C. M., & Sarstedt, M. (2023). PLS-SEM's most wanted guidance. *International Journal of Contemporary Hospitality Management*, *35*(1), 321-346.

Chan, T. K., Cheung, C. M., & Lee, Z. W. (2017). The state of online impulse-buying research: A literature analysis. *Information & Management*, *54*(2), 204-217.

Chen, K., & Yen, D. C. (2004). Improving the quality of online presence through interactivity. *Information & Management*, *42*(1), 217-226.

Choung, H., David, P., & Ross, A. (2022). Trust in AI and Its Role in the Acceptance of AI Technologies. *International Journal of Human–Computer Interaction*, *39*, 1727-1739. https://doi.org/10.1080/10447318.2022.2050543

Das, T., & Teng, B.-S. (2004). The Risk-Based View of Trust: A Conceptual Framework. *Journal of Business and Psychology*, *19*, 85-116. https://doi.org/10.1023/B:JOBU.0000040274.23551.1B

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly*, 319-340.

Ding, Y., & Najaf, M. (2024). Interactivity, humanness, and trust: a psychological approach to AI chatbot adoption in e-commerce. *BMC psychology*, *12*(1), 595. https://doi.org/10.1186/s40359-024-02083-z

Dorton, S., & Harper, S. (2022). A Naturalistic Investigation of Trust, AI, and Intelligence Work. *Journal of Cognitive Engineering and Decision Making*, *16*, 222-236. https://doi.org/10.1177/15553434221103718

Dwivedi, Y. K., Hughes, L., Wang, Y., Alalwan, A. A., Ahn, S. J., Balakrishnan, J., Barta, S., Belk, R., Buhalis, D., & Dutot, V. (2023). Metaverse marketing: How the metaverse will shape the future of consumer research and practice. *Psychology & Marketing*, *40*(4), 750-776.

Flavián, C., Ibáñez-Sánchez, S., & Orús, C. (2019). The impact of virtual, augmented and mixed reality technologies on the customer experience. *Journal of business research*, *100*, 547-560.

Goh, E. S., Sunar, M., & Ismail, A. (2019). 3D Object Manipulation Techniques in Handheld Mobile Augmented Reality Interface: A Review. *IEEE Access*, *7*, 40581-40601. https://doi.org/10.1109/ACCESS.2019.2906394

Gualtieri, L., Phillips, J., Rosenbluth, S., & Synoracki, S. (2018). Digital literacy: a barrier to adoption of connected health technologies in older adults. *Iproceedings*, *4*(2), e11803.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European business review*, *31*(1), 2-24.

Henseler, J., Dijkstra, T. K., Sarstedt, M., Ringle, C. M., Diamantopoulos, A., Straub, D. W., Ketchen Jr, D. J., Hair, J. F., Hult, G. T. M., & Calantone, R. J. (2014). Common beliefs and reality about PLS: Comments on Rönkkö and Evermann (2013). *Organizational research methods*, *17*(2), 182-209.

Hmoud, M., Daher, W., & Ayyoub, A. (2025). The Impact of AI, XR, and Combined AI-XR on Student Satisfaction: A Moderated Mediation Analysis of Engagement and Learner Characteristics. *IEEE Access*.

Jacoby, J. (2002). Stimulus-organism-response reconsidered: an evolutionary step in modeling (consumer) behavior. *Journal of consumer psychology*, *12*(1), 51-57.

Jain, K., & Raghuram, J. (2024). Gen-AI integration in higher education: Predicting intentions using SEM-ANN approach. *Educ. Inf. Technol.*, *29*, 17169-17209. https://doi.org/10.1007/s10639-024-12506-4

Kabir, Z. S., & Kang, K. (2025). An Interaction–Engagement–Intention Model: How Artificial Intelligence and Augmented Reality Transform the User–Platform Interaction Paradigm. *Electronics*, *14*(12), 2499. https://www.mdpi.com/2079-9292/14/12/2499

Kenesei, Z., Kökény, L., Ásványi, K., & Jászberényi, M. (2025). The central role of trust and perceived risk in the acceptance of autonomous vehicles in an integrated UTAUT model. *European Transport Research Review*, *17*(1), 8. https://doi.org/10.1186/s12544-024-00681-x

Kim, J., Kang, S., & Bae, J. (2022). Human likeness and attachment effect on the perceived interactivity of AI speakers. *Journal of business research*, *144*, 797-804.

Leung, W. K., Cheung, M. L., Chang, M. K., Shi, S., Tse, S. Y., & Yusrini, L. (2022). The role of virtual reality interactivity in building tourists' memorable experiences and post-adoption intentions in the COVID-19 era. *Journal of Hospitality and Tourism Technology*, *13*(3), 481-499.

Li, M., Dong, Z., & Chen, X. (2012). Factors influencing consumption experience of mobile commerce: A study from experiential view. *Internet Research*, *22*(2), 120-141.

Liu, J., Zhu, Y., Cui, Y., & Zhang, L. (2023). A study of the influence of environmental stimuli on behavioral intentions in the tourism experience of memorial spaces. *Asia Pacific Journal of Tourism Research*, *28*, 591-609. https://doi.org/10.1080/10941665.2023.2255297

Manthiou, A., Ayadi, K., Lee, S., Chiang, L., & Tang, L. (2017). Exploring the roles of self-concept and future memory at consumer events: The application of an extended Mehrabian–Russell model. *Journal of Travel & Tourism Marketing*, *34*(4), 531-543.

Mehrabian, A., & Russell, J. A. (1974). *An approach to environmental psychology*. the MIT Press.

Nazaretsky, T., Mejia-Domenzain, P., Swamy, V., Frej, J., & Käser, T. (2025). The Critical Role of Trust in Adopting AI-Powered Educational Technology for Learning: An Instrument for Measuring Student Perceptions. *Computers and Education: Artificial Intelligence*, *8*, 100368. https://doi.org/10.1016/j.caeai.2025.100368

Rana, M. M., Siddiqee, M. S., Sakib, M. N., & Ahamed, M. R. (2024). Assessing AI adoption in developing country academia: A trust and privacy-augmented UTAUT framework. *Heliyon*, *10*(18).

Rauschnabel, P. A., Babin, B. J., tom Dieck, M. C., Krey, N., & Jung, T. (2022). What is augmented reality marketing? Its definition, complexity, and future. In (Vol. 142, pp. 1140-1150): Elsevier.

Rodríguez-Torrico, P., San-Martín, S., & San José-Cabezudo, R. (2019). What drives M-shoppers to continue using mobile devices to buy? *Journal of Marketing theory and Practice*, *27*(1), 83-102.

Saveljeva, J. (2025). Trust and Risk Management Interplay: A Review in the Digital Context. 189-196. https://doi.org/10.5220/0013344200003956

Shang, Q., Ma, H., Wang, C., & Gao, L. (2023). Effects of background fitting of e-commerce live streaming on consumers' purchase intentions: a cognitive-affective perspective. *Psychology Research and Behavior Management*, 149-168.

Shao, Z., & Chen, K. (2021). Understanding individuals' engagement and continuance intention of MOOCs: the effect of interactivity and the role of gender. *Internet Research*, *31*(4), 1262-1289.

Shi, W., Rumokoy, F., & Frank, B. (2025). Customer loyalty through augmented reality apps: quality attributes, market differences, and trust as a mediator. *Total Quality Management & Business Excellence*, *36*, 759-787. https://doi.org/10.1080/14783363.2025.2477169

Singh, N. (2024). Data Security and Consumer Trust in Fintech Innovations using Technology Adoption Method. *INTERANTIONAL JOURNAL OF SCIENTIFIC RESEARCH IN ENGINEERING AND MANAGEMENT*. https://doi.org/10.55041/ijsrem33015

Vazquez, D., Dennis, C., & Zhang, Y. (2017). Understanding the effect of smart retail brand–Consumer communications via mobile instant messaging (MIM)–An empirical study in the Chinese context. *Computers in human behavior*, *77*, 425-436.

Wahshat, H. A., Al-Rousan, R., Al-Haithami, W. A., Saany, S. A., Mohamad, F. S., & Kumar, R. (2023). Current Problems and Proposed Solutions for the Electronic Commerce Sector. *2023 International Conference on Computer Science and Emerging Technologies (CSET)*, 1-6. https://doi.org/10.1109/CSET58993.2023.10346777

Wang, J., Wen, S., & Xue, J. (2023). Unraveling the influential mechanisms of social commerce overloads on user disengagement: The buffer effect of guanxi. *Psychology Research and Behavior Management*, 1921-1945.

Wanniarachchi, D., & Misra, A. (2025). MIMIC: AI and AR-enhanced Multi-Modal, Immersive, Relative Instruction Comprehension. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, *9*, 1-34. https://doi.org/10.1145/3712268

Wünderlich, N., Wangenheim, F., & Bitner, M. (2013). High Tech and High Touch. *Journal of Service Research*, *16*, 20-23. https://doi.org/10.1177/1094670512448413

Xie, J., Ye, L., Huang, W., & Ye, M. (2021). Understanding FinTech Platform Adoption: Impacts of Perceived Value and Perceived Risk. *J. Theor. Appl. Electron. Commer. Res.*, *16*, 1893-1911. https://doi.org/10.3390/JTAER16050106

Yang, Y., Cho, H.-K., & Kim, M.-Y. (2025). A Study on Factors Affecting the Continuance Usage Intention of Social Robots with Episodic Memory: A Stimulus–Organism–Response Perspective. *Applied Sciences*, *15*(10), 5334. https://www.mdpi.com/2076-3417/15/10/5334

Yu, T., Tian, Y., Chen, Y., Huang, Y., Pan, Y., & Jang, W. (2025). How Do Ethical Factors Affect User Trust and Adoption Intentions of AI-Generated Content Tools? Evidence from a Risk-Trust Perspective. *Systems*, *13*(6), 461. https://www.mdpi.com/2079-8954/13/6/461

Yuan, Y.-P., Liu, L., Tan, G., & Ooi, K. (2024). Do consumers' perceptions of algorithms and trusting beliefs in providers affect perceived structural assurances of AI-powered applications? *Telematics Informatics*, *94*, 102188. https://doi.org/10.1016/j.tele.2024.102188

Appendix: 1

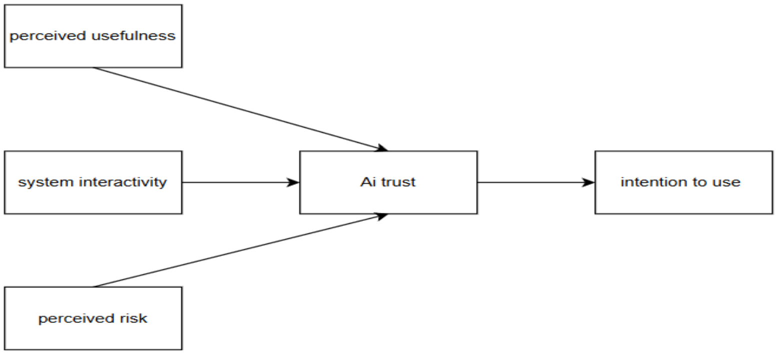

Figure 1: Conceptual Framework
Source: Own

Appendix: 2

Table 1: Demographics Analysis

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	MALE	123	49,8	49,8	49,8
	FEMALE	124	50,2	50,2	100,0
	Total	247	100,0	100,0	
Age					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	UP TO 25	93	37,7	37,7	37,7
	26-35	87	35,2	35,2	72,9
	36-45	21	8,5	8,5	81,4
	46-55	45	18,2	18,2	99,6
	OVER 55	1	0,4	0,4	100,0
	Total	247	100,0	100,0	
EDUCATION					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	TECHNICAL.DIPLOMA	3	1,2	1,2	1,2
	LANGUAGE COURSE	14	5,7	5,7	6,9
	BACHELOR	48	19,4	19,4	26,3
	MASTER	172	69,6	69,6	96,0
	PHD	10	4,0	4,0	100,0
	Total	247	100,0	100,0	

Appendix: 3

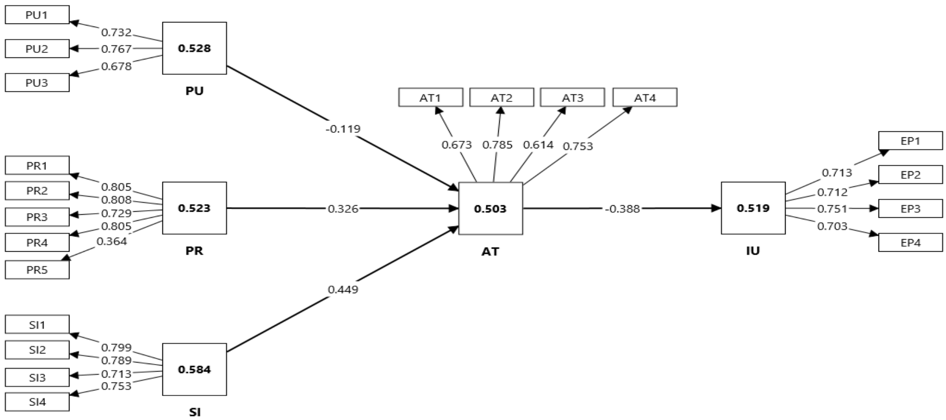

Figure 2: Measurement Model assessment

Table 2: COVERGENT VALIDITY

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AT	0,667	0,675	0,8	0,503
IU	0,693	0,696	0,812	0,519
PR	0,748	0,785	0,838	0,523
PU	0,551	0,554	0,77	0,528
SI	0,764	0,773	0,848	0,584

Appendix: 4

Table 3: DISCRIMINANT VALIDITY

HTMT	AT	IU	PR	PU	SI
AT					
IU	0,559				
PR	0,754	0,399			
PU	0,538	0,873	0,462		
SI	0,818	0,434	0,476	0,382	

Appendix: 5

Table 4: FORNELL LARCKER

	AT	IU	PR	PU	SI
AT	0,709				
IU	-0,388	0,72			
PR	0,526	-0,278	0,723		
PU	-0,329	0,543	-0,297	0,727	
SI	0,598	-0,324	0,366	-0,252	0,764

Appendix: 6

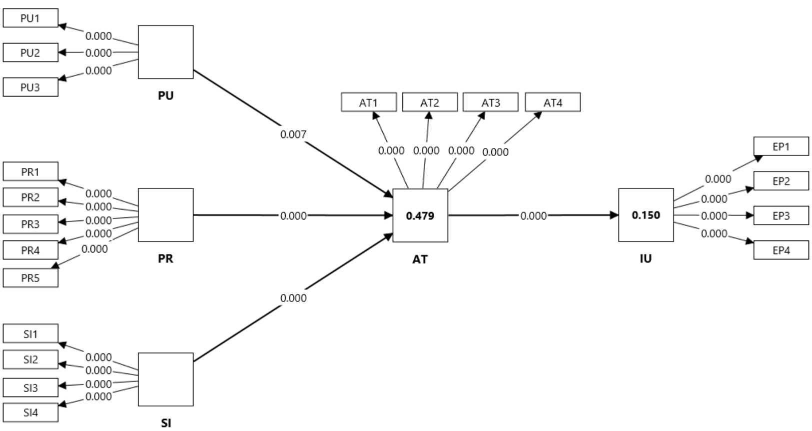

Figure 4: Structural model assessmement

Table 6: Direct effect

DIRECT EFFECT					
	Original sample (O)	**Sample means (M)**	**Standard deviation (STDEV)**	**T statistics (|O/STDEV|)**	**P values**
AT -> IU	-0,388	-0,395	0,045	8,587	< 0.001
PR -> AT	0,326	0,329	0,07	4,661	< 0.001
PU -> AT	-0,119	-0,122	0,044	2,677	0,007
SI -> AT	0,449	0,451	0,056	8,061	< 0.001
SPECIFIC IN-DIRECT EFFECT					
	Original sample (O)	**Sample means (M)**	**Standard deviation (STDEV)**	**T statistics (|O/STDEV|)**	**P values**
PR -> AT -> IU	-0,126	-0,13	0,031	4,11	< 0.001
PU -> AT -> IU	0,046	0,049	0,02	2,258	0,024
SI -> AT -> IU	-0,174	-0,178	0,029	6,089	< 0.001

Appendix: 7

Table 7: Hypothesis

Hypothesis	Relationship	Estimate	T statistics	P values	VIF	Test Result
H1a	System Interactivity → AI Trust	0,449	8,06	< 0.001	1,5	Support
H1b	System Interactivity → Intention to Use	0,1	1,9	0,06	1,6	Marginal
H2a	Perceived Usefulness → AI Trust	0,119	2,68	0,007	1,7	Support
H2b	Perceived Usefulness → Intention to Use	0,543	3,5	0,001	1,65	Support
H3a	Perceived Risk → AI Trust	-0,326	4,66	< 0.001	1,8	Support
H3b	Perceived Risk → Intention to Use	-0,05	1	0,32	1,55	Not Support
H4a	System Interactivity → AI Trust → Intention to Use	0,174	6,09	< 0.001	1,45	Support
H4b	Perceived Usefulness → AI Trust → Intention to Use	0,046	2,26	0,024	1,5	Support
H4c	Perceived Risk → AI Trust → Intention to Use	-0,126	4,11	< 0.001	1,4	Support

Note: P-values reported as < 0.001 indicate minimal values (e.g., < 0.0005), as the software returned values approaching zero. For interpretative clarity, exact values below 0.001 are shown in this standardized format.

Appendix: 8

Table 8: Predictive Analysis

	R-SQUARE	Q^2predict	RMSE	MAE	Average loss difference	t value	p value
AT	**0,479**	0,45	0,748	0,559	-0,24	6,034	0,000
IU	**0,15**	0,155	0,927	0,735	-0,061	5,475	0,000
Overall					-0,15	7,112	0,000

Appendix: 9

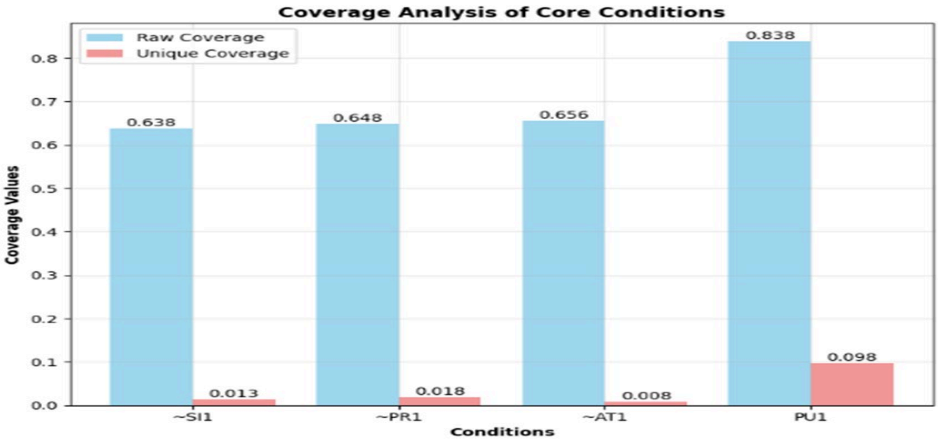

Figure 4: Coverage Analysis

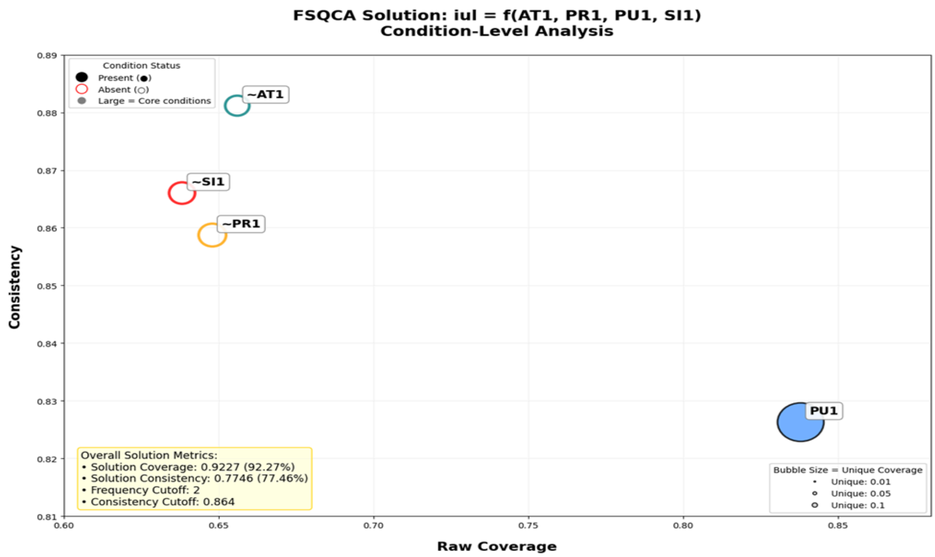

Figure 5: Condition level analysis