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Trust, Transparency, and Learner Data Use in Community Education Platforms

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ABSTRACT

This study examines how trust and transparency influence learner acceptance of data use in community education platforms. The study is designed to collect data from approximately 3,000 learners using 15 community education platforms, together with platform policy documents, consent forms, user activity records, and administrator interviews. The dataset is expected to include around 3,000 learner questionnaires, 150 platform policy documents, 500 consent-form samples, 200,000 anonymized platform-use logs, and 45 administrator interviews. The study measures data-use transparency, consent clarity, privacy concern, perceived institutional responsibility, algorithmic explanation, platform trust, willingness to share learning data, and continued platform-use intention. Quantitative methods include reliability testing, confirmatory factor analysis, structural equation modeling, logistic regression, moderation analysis, and multi-group comparison to examine whether transparency reduces privacy concerns and increases learner trust. Platform-use logs are also analyzed to compare self-reported trust with actual participation behavior, including login frequency, course completion, feedback submission, and data-sharing choices. The innovation of this study lies in connecting learner data governance with measurable trust and behavioral acceptance, showing that transparent data practices are not only ethical requirements but also important conditions for sustainable platform-based community education.

1. Introduction

Community education platforms have become an important part of adult learning, vocational training, public education, continuing education, and local skill development. Unlike conventional school-based learning systems, these platforms often serve highly heterogeneous populations whose age, educational background, employment status, digital literacy, and learning goals may differ substantially. During routine operation, platforms continuously collect learner profiles, course selections, login records, assessment results, feedback, communication histories, and other forms of behavioral data. These data can support course planning, learner support, resource allocation, service evaluation, and personalized learning. At the same time, they may also be used for learner profiling, behavioral prediction, automated recommendation, institutional monitoring, or data sharing with external service providers. The increasing use of learner data therefore raises questions about who can access the data, how long they are retained, what purposes they may be used for, and whether learners have meaningful control over subsequent uses. Previous research on online learning has shown that learner experience is shaped not only by system functionality but

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also by personal, cultural, institutional, and policy conditions (Park & Choi, 2025). Related research on public education has further emphasized the importance of systematic monitoring for evaluating teaching quality and validating educational equity (Lin, Spivack, et al., 2026). Such monitoring can improve institutional accountability, but it also increases the importance of clearly defining how educational data are collected, interpreted, and governed. This issue is particularly relevant in community education, where participation is often voluntary and learners may reduce their participation or leave a platform when they perceive its data practices as unclear, intrusive, or difficult to control. Trust is therefore a central issue in the governance of community education data. Research on learning analytics has shown that privacy concern is closely associated with perceived risk, perceived control, institutional trust, and willingness to disclose personal information (Drăgoi et al., 2026). Privacy in education, however, cannot be reduced to technical security or compliance procedures. It also concerns institutional power, responsibility, learner autonomy, and the extent to which individuals are able to understand and influence decisions involving their data (Du, 2025). Reviews of the learning analytics literature have noted that privacy is often defined inconsistently across legal, technical, and educational studies, which makes it difficult to connect policy requirements with actual learner experience (Zhang et al., 2026). Similar reviews have identified continuing gaps between abstract privacy principles and their implementation in educational practice (García-López et al., 2025). These problems may be more pronounced in community education because learners are not a homogeneous user group. Older adults, learners with limited formal education, newly employed workers, and people with relatively low digital literacy may interpret privacy notices and platform controls differently. A governance mechanism that appears adequate from a technical or legal perspective may therefore remain ineffective if learners cannot understand what information is collected, why it is needed, or what choices are available to them.

Transparency is commonly proposed as one mechanism for reducing this gap. In educational platforms, transparency may involve readable privacy notices, simplified consent procedures, explanations of data use, information about automated recommendations, and access to personal records or data-management settings. User-centered research has shown that learners should not be treated merely as data subjects but should also participate in the design and evaluation of privacy and transparency mechanisms (Qi & Qiao, 2026). Trust in learning analytics depends partly on system quality, but it is also influenced by the way institutions communicate their purposes, procedures, and responsibilities to learners (Su & Wu, 2026). Direct information about data practices can increase awareness of how personal information is processed (King et al., 2025), while explanations of automated outputs may help users understand and evaluate decisions generated by data-driven systems (Shao, 2026). Transparency, however, should not be understood simply as the provision of more information. Long privacy policies, highly technical terminology, fragmented consent interfaces, and broad statements about possible future data use may formally disclose institutional practices without producing meaningful understanding. Information becomes useful only when it is sufficiently clear, relevant to the learner's situation, and connected to choices that can actually be exercised. Transparency should therefore be considered not only in terms of information availability but also in terms of information comprehensibility, practical relevance, and perceived controllability. Consent presents a related governance challenge. Many educational platforms require learners to accept standard terms before account registration or course participation, yet formal acceptance does not necessarily represent informed and voluntary consent. Learners may agree because access to the platform is necessary for participation, because the alternatives are unclear, or because they do not fully understand how their data may later be analyzed or shared. Privacy concern is also context-dependent and can vary according to the sensitivity of the data, the purpose for which the data are used, and the identity of the organization or person receiving them (Xiong & Zeng, 2026). Consequently, the same learner may be willing to provide course-selection data for instructional improvement but unwilling to permit the same information to be used for commercial profiling or transferred to third parties. Research on educational technology governance has also suggested that institutional review may focus heavily on basic regulatory compliance while relying excessively on assurances provided by technology vendors (Katterbauer & Özbay, 2026). This creates a potential gap between formal compliance and perceived institutional responsibility. Clear procedures may improve trust, but readable consent forms alone may have limited effects when learners doubt whether the institution has the competence, authority, or willingness to protect their information (Hong et al., 2026b). Consent clarity must therefore be considered together with institutional responsibility rather than treated as an isolated interface feature. These governance conditions are also closely connected to technology acceptance and continued participation. Studies of educational technologies have reported that trust can increase intention to use a system, whereas privacy concern can reduce willingness to adopt or continue using it (Balaskas et al., 2025; Huang, Yin, et al., 2026). Trust has additionally been associated with perceived value, readiness, and willingness to adopt emerging educational technologies (Zhang et al., 2025). These relationships may become more complicated as educational platforms increasingly incorporate automated recommendation, prediction, and decision-support tools. Privacy, security, algorithmic bias, and insufficient explanation remain persistent concerns when automated systems process learner information or influence educational opportunities (English, 2025; Yao et al., 2026). Importantly, learners are unlikely to respond to these practices in the same way. Gender, cultural background, digital experience, and national context can influence privacy perceptions, trust formation, and disclosure behavior (Hong et al., 2026a; Lin, Chen, et al., 2026). In China, recent discussions of educational data governance have similarly called for clearer limits on data use, more understandable privacy notices, and stronger mechanisms for learner control (Li et al., 2026; Salendab, 2026). These differences indicate that a governance model evaluated only at the aggregate level may conceal important variation among learner groups. Multi-group comparison is therefore necessary for determining whether the same transparency or consent mechanisms operate consistently across different types of community learners. Despite this growing literature, several methodological limitations remain. Much of the existing evidence comes from university students, individual institutions, or narrowly defined online learning settings. Community education has received comparatively limited attention even though its participants are often more diverse in age, education, occupation, and digital experience. Existing studies also rely heavily on cross-sectional questionnaires and self-reported intention, making it difficult to determine whether reported trust is reflected in actual platform behavior. Small samples, limited control groups, and insufficient integration of behavioral records remain common limitations in research on privacy and learning analytics (Ngulube & Ncube, 2025; Wu, Wu, et al., 2026). In addition, privacy policies and consent documents are frequently analyzed separately from learner perceptions, while system-use records are evaluated separately from institutional governance. This fragmentation makes it difficult to determine whether written policies, perceived transparency, institutional responsibility, and actual learner behavior are mutually consistent. A learner may, for example, report relatively high institutional trust while declining optional data sharing, or may continue logging into a platform despite expressing substantial privacy concern. Conversely, a well-written privacy policy may satisfy formal governance requirements without producing observable differences in participation. Understanding these discrepancies requires a research design that combines institutional documents, learner perceptions, and behavioral evidence rather than relying on a single source of data.

The present study addresses these limitations by examining approximately 3,000 learners across 15 community education platforms and integrating questionnaires, privacy policies, consent forms, platform-use logs, and administrator interviews within a unified research design. The study aims to determine how transparency, consent clarity, privacy concern, and perceived institutional responsibility jointly shape learner trust and data-sharing intention, and whether these relationships differ across learner groups. Confirmatory factor analysis is used to assess the measurement structure of the principal constructs, while structural equation modeling is applied to estimate the relationships among governance conditions, privacy perceptions, trust, and willingness to share data. Logistic regression further examines whether self-reported perceptions correspond to observable behavioral outcomes, including login frequency, course completion, feedback submission, and actual data-sharing choices. Multi-group analysis is used to identify possible differences associated with demographic characteristics, educational background, and digital experience. By combining written data-governance rules with learner perceptions and real platform behavior, the study moves beyond an intention-only approach and evaluates whether formal transparency and consent mechanisms are reflected in actual participation. The research also extends privacy and trust research from conventional university-based learning environments to community education, where participation is more voluntary and learner characteristics are more heterogeneous. Its contribution is therefore both methodological and practical: methodologically, it provides an integrated framework for connecting institutional policy, perceived governance quality, trust, and behavioral evidence; practically, it can help community education providers identify which aspects of transparency, consent, and institutional responsibility are most relevant to maintaining learner trust. More broadly, the study provides evidence for designing data-governance mechanisms that are not only legally compliant but also understandable, credible, and actionable for diverse learner populations, thereby supporting more responsible, inclusive, and sustainable use of learner data in community education.

2. Materials and Methods

2.1 Sample and Study Setting

The study included about 3,000 adult learners from 15 community education platforms. The platforms offered vocational training, digital skills courses, language classes, cultural programs, and public learning services. Learners were included when they were at least 18 years old, had used the platform for at least four weeks, and had completed one or more course activities. Staff accounts, test accounts, automated accounts, and surveys with more than 20% missing data were excluded. The dataset contained about 3,000 questionnaires, 150 policy documents, 500 consent-form samples, 200,000 anonymous activity records, and 45 administrator interviews. Learner age, education, digital experience, course type, length of platform use, and privacy knowledge were recorded. All personal identifiers were removed before analysis, and each learner received an anonymous code.

2.2 Study Design and Comparison Groups

A cluster-randomized field study was used to test the effect of clear data-use information. A total of 120 course groups were assigned within each platform to an intervention group or a comparison group. The intervention group received a short notice that explained what data were collected, why the data were needed, how long they were stored, who could access them, and how learners could change their choices. The notice also gave a simple explanation of automated course recommendations. The comparison group received the standard privacy policy and consent form already used by the platform. Each group included about 1,500 learners. The intervention lasted eight weeks. Course content, platform functions, and teaching support remained the same in both groups. Assignment at the course-group level reduced information exchange between the two groups and allowed the effect of the notice to be measured under normal learning conditions.

2.3 Measurement and Quality Control

Data-use transparency, consent clarity, privacy concern, institutional responsibility, algorithm explanation, platform trust, willingness to share learning data, and continued-use intention were measured with five-point Likert scales. Each measure contained three to five items taken from recent studies on privacy, trust, and technology use. Actual behavior was measured through login frequency, course completion, feedback submission, optional data-sharing choices, and continued platform use. Policy documents and consent forms were coded for data purpose, storage period, third-party sharing, learner rights, withdrawal options, and automated decisions. A pilot study with 120 learners was completed before the main survey, and unclear items were revised. Internal consistency was accepted when Cronbach's alpha and composite reliability were above 0.70. Two researchers coded 20% of the policy documents independently. Agreement was accepted when Cohen's kappa was above 0.80. Duplicate records, unusual login events, and system-generated activity were removed. Platform timestamps were checked against server records, and 5% of the activity logs were reviewed manually.

2.4 Data Processing and Model Formulation

Survey responses, policy scores, consent records, and platform logs were linked through anonymous learner and platform codes. Activity measures were converted to a common 30-day period because observation time differed among learners. Values above the 99th percentile were checked for repeated system events or unusual use before removal. A platform transparency index was calculated from five policy areas:

$$TI_p=\frac{C_p+P_p+R_p+W_p+E_p}{5}$$

Where TI_p is the transparency score for platform p, C_p is the clarity of data collection, P_p is the explanation of data purpose, R_p is the storage and sharing score, W_p is the learner-rights score, and E_p is the algorithm explanation score. Each part was converted to a scale from 0 to 100. Optional data sharing was tested with logistic regression:

$$\log\left(\frac{P(Y_i=1)}{1-P(Y_i=1)}\right)=\beta_0+\beta_1 T_i+\beta_2 TR_i+\beta_3 PC_i+\beta_4 G_i+\sum_{k=1}^{m}\gamma_k X_{ki}$$

where Y_i shows whether learner i accepted optional data sharing, T_i is perceived transparency, TR_i is platform trust, PC_i is privacy concern, G_i is group assignment, and X_{ki} represents learner and platform control variables.

2.5 Statistical Analysis

Descriptive statistics were used to summarize learner and platform features. Reliability tests and confirmatory factor analysis were used to assess the measurement scales. Model fit was checked with the comparative fit index, Tucker–Lewis index, root mean square error of approximation, and standardized root mean square residual. Structural equation modeling tested the links among transparency, consent clarity, privacy concern, institutional responsibility, trust, and continued-use intention. Logistic regression tested optional data sharing, course completion, and continued platform use. Moderation analysis examined whether age, digital experience, privacy knowledge, and course type changed the relation between transparency and trust. Multi-group analysis compared results across learner and platform groups. Intervention effects were estimated by intention-to-treat analysis. Standard errors were adjusted for learners grouped within courses and platforms. Missing survey data were handled with full-information maximum likelihood. Results were reported as standardized coefficients, odds ratios, 95% confidence intervals, and ppp-values. Statistical significance was set at $p<0.05$.

3. Results and Discussion

3.1 Policy Clarity and Learner Understanding

After data screening, 2,872 valid questionnaires were retained. The intervention group included 1,437 learners, and the comparison group included 1,435 learners. The scales showed good reliability. Cronbach's alpha ranged from 0.80 to 0.92, while composite reliability ranged from 0.83 to 0.94. All average variance extracted values were above 0.50. The confirmatory factor model also showed a good fit ($\chi^2/df=2.71$, CFI = 0.951, TLI = 0.943, RMSEA = 0.039, and SRMR = 0.036). The review of 150 policy documents showed clear differences among the 15 platforms. The mean transparency score was 64.7, with platform scores ranging from 42.8 to 84.6. Most platforms explained why learner data were collected. However, fewer than half gave a clear storage period or withdrawal process. Only four platforms explained how learner data affected automated recommendations. Learners understood the policies better when the notices used short sentences, clear headings, and separate consent choices. Policy length was negatively related to consent understanding ($r=-0.29, p<0.001$). This finding shows that a long policy may meet formal rules but still fail to provide useful information (Alshammari & Al-Mamary, 2025; Huang, Xu, et al., 2026). Alshammari et al. (2026) also identified consent, data storage, algorithm explanations, and institutional responsibility as major concerns in educational technology use.

3.2 Relations among Transparency, Privacy Concern, and Trust

The structural equation model explained 61% of the variance in platform trust and 49% of the variance in willingness to share learning data. Consent clarity had a positive effect on perceived transparency ($\beta=0.52, p<0.001$). Transparency reduced privacy concern ($\beta=-0.31, p<0.001$) and improved perceptions of institutional responsibility ($\beta=0.46, p<0.001$). Institutional responsibility had the strongest direct relation with trust ($\beta=0.44, p<0.001$). Algorithm explanation also increased trust ($\beta=0.24, p<0.001$), while privacy concern reduced it ($\beta=-0.28, p<0.001$). The direct relation between transparency and trust was weaker but remained significant ($\beta=0.14, p=0.018$). The main relations are shown in Fig. 1. The mediation test showed that transparency improved trust mainly by reducing privacy concern and increasing confidence in platform responsibility (Behara, 2026; Wu, Zhang, et al., 2026). Trust was then positively related to data-sharing intention ($\beta=0.41, p<0.001$) and continued-use intention ($\beta=0.47, p<0.001$). Huang et al. (2026) also found that privacy concern reduced knowledge sharing and online learning. Behara et al. (2026) reported that trust and perceived risk affected technology acceptance through indirect paths. These findings show that information alone does not create trust. Learners must also believe that data use is limited, controlled, and open to review.

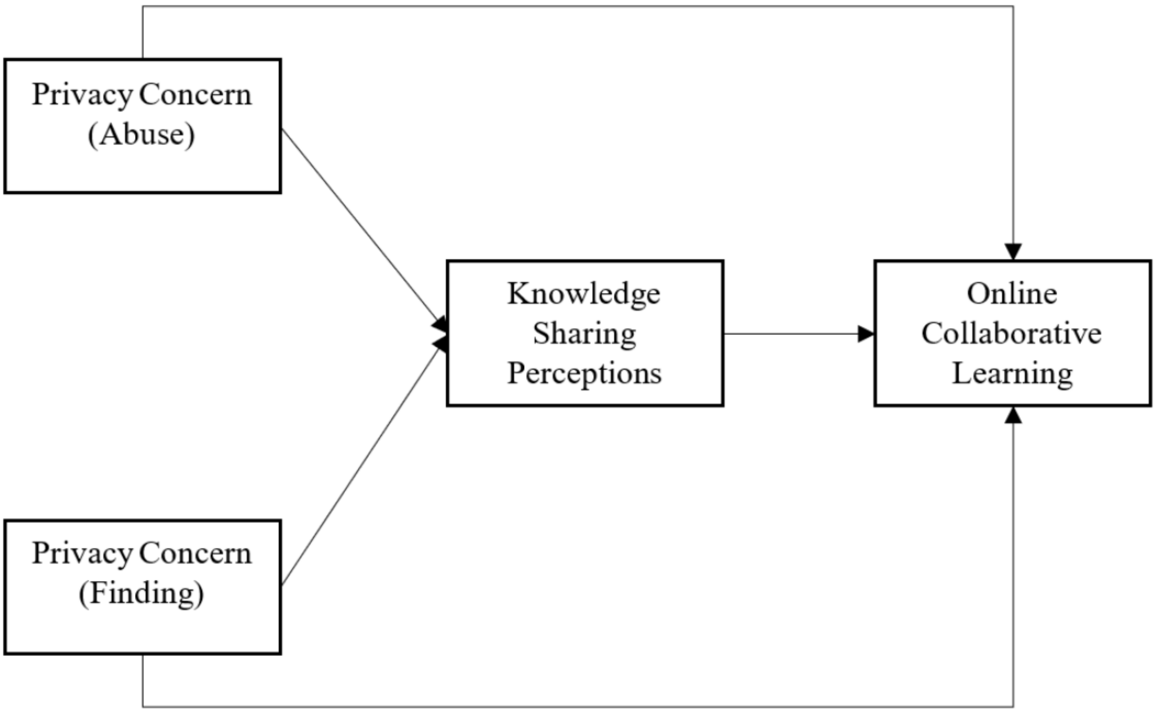

Fig. 1. Links among data transparency, privacy concern, platform trust, and learner acceptance.

3.3 Effects of the Clear Data-Use Notice

After the eight-week intervention, the mean consent-clarity score was 4.18 in the intervention group and 3.43 in the comparison group. The adjusted difference was 0.69 points (95% CI: 0.62–0.76, $p<0.001$). Mean platform trust was also higher in the intervention group than in the comparison group (4.03 vs. 3.58). The adjusted difference was 0.42 points (95% CI: 0.35–0.49, $p<0.001$). Privacy concern decreased from 3.37 to 2.93 among learners who received the clear notice, while little change occurred in the comparison group. Optional data sharing was accepted by 63.7% of the intervention group and 48.9% of the comparison group. After age, education, digital experience, course type, and platform differences were controlled, the notice increased the odds of optional data sharing (OR = 1.76, 95% CI: 1.49–2.09). The effect was stronger among learners aged 45 years or older and those with limited digital experience. Short explanations of automated recommendations also received higher trust scores than technical descriptions. Wu et al. (2026) found that explanation methods produced different levels of trust and satisfaction in learning analytics. Huang et al. (2026) also reported that perceived benefits, anxiety, and trust-building methods affected the acceptance of educational technologies. These results suggest that platforms should use short notices written for different learner groups rather than one standard policy for all users.

3.4 Reported Trust and Actual Use

Platform logs showed that trust was related to actual behavior, but the relation was not strong enough to predict every choice. A one-point increase in trust was linked to higher odds of course completion (OR = 1.29, 95% CI: 1.18–1.41), feedback submission (OR = 1.25, 95% CI: 1.14–1.37), optional data sharing (OR = 1.47, 95% CI: 1.34–1.62), and continued platform use (OR = 1.33, 95% CI: 1.21–1.46). Learners with high trust logged in 16.8% more often than learners with low trust. However, 22.4% of high-trust learners still rejected optional data sharing. At the same time, 29.6% of low-trust learners continued to use the platform during the follow-up period. As shown in Fig. 2, the largest gap between reported trust and actual behavior occurred in optional data sharing. The smallest gap occurred in course completion. Learners may continue a useful course even when they have privacy concerns. However, they are less willing to approve data uses that are not required for learning. This finding shows that platform use should not be treated as full acceptance of all data practices. Zhang et al. (2021) also found that privacy concern can limit knowledge sharing even when learners remain active in online education. Trust surveys should therefore be combined with consent choices, platform logs, and later use records. The study was limited by the eight-week follow-up period and differences among platform functions (Alkhateeb et al., 2026; Zhang et al., 2021). Longer studies are needed to test whether trust remains stable and whether learners later change their data-sharing choices.

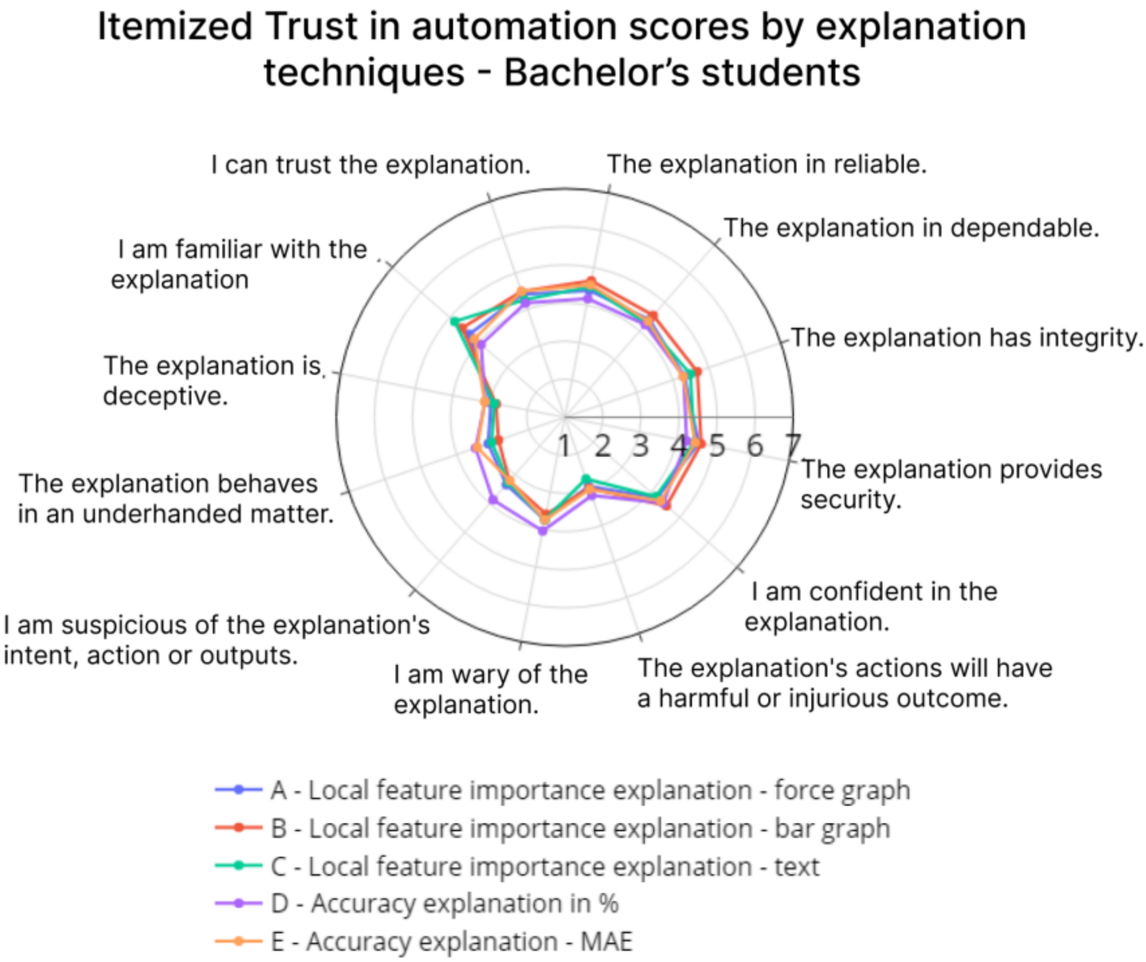

Fig. 2. Reported trust and actual learner behavior under standard and clear data-use notices.

4. Conclusion

This study found that clear information about data use can increase learner trust and acceptance in community education platforms. Learners who received short and simple notices showed better understanding of consent, lower privacy concern, stronger trust, and greater willingness to share learning data. Trust was also linked to course completion, feedback submission, and continued platform use, although reported trust did not always match actual behavior. The main contribution of this study is the combined use of surveys, policy documents, consent forms, platform logs, and administrator interviews to compare learner views with real actions. The results show that transparency is most effective when platforms explain data collection, storage, sharing, learner rights, and automated recommendations in clear language. These findings can support the design of privacy notices, consent tools, and data-management rules for community education platforms. However, the study covered only 15 platforms and followed learners for eight weeks. Platform functions also differed, and some measures were based on self-reported data. Future studies should include more platforms, use longer follow-up periods, and examine how trust changes as learners gain more experience with data-use policies.

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