Digital design tool accessibility drives innovation disparities across user populations

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Abstract

Digital design tools have transformed creative innovation, yet significant accessibility disparities persist across user populations. Here we examine how user background characteristics influence design tool utilization and innovation outcomes through a comprehensive study of 1,095 design practitioners and 111 educators across 69 institutions in China. We find that users with advanced technical backgrounds demonstrate 65% higher tool usage frequencies and achieve innovation quality scores 25 points higher than users with limited technical experience. Institutional environments show modest effects on outcomes, failing to effectively bridge accessibility gaps. Our analysis reveals that technical background explains 42% of variance in innovation quality, with each additional weekly session associated with 8.64-point quality improvements. These findings establish a theoretical framework for design tool accessibility and provide evidence-based strategies for promoting innovation democratization in the digital era.

Keywords: Digital design divide,Technical background,Innovation quality,Institutional environment

1 Introduction

The digital transformation of design practice has fundamentally altered creative workflows, with sophisticated tools now central to innovation processes across industries[1, 2]. Contemporary design environments integrate computer-aided design software, collaborative platforms, and artificial intelligence-powered assistants, theoretically democratizing access to professional-grade capabilities[3, 4]. However, significant disparities persist in how different user populations engage with these technologies, creating what we term the ”digital design divide”[5, 6]. Unlike traditional design methods requiring primarily artistic skill and domain knowledge, digital environments demand additional competencies in software navigation, interface comprehension, and technical troubleshooting[7, 8]. These requirements generate accessibility barriers that may systematically exclude certain user populations from innovation opportunities[9, 10]. Recent studies in human- computer interaction highlight the critical importance of user background characteristics in determining technology adoption outcomes[11, 12], yet limited research has examined these relationships specifically within design innovation contexts. The institutional context within which design tools are deployed plays a crucial role in shaping user experiences[13, 14]. Educational institutions, creative agencies, and innovation laboratories serve as intermediary environments that can either amplify or mitigate individual-level accessibility barriers[15, 16]. However, the extent to which institutional environments actually fulfill this equalizing function remains empirically unclear. Here we address this gap through a comprehensive investigation of digital design tool accessibility and innovation disparities. Our study quantifies the extent and nature of accessibility barriers while examining the role of institutional environments in mediating these relationships. We develop evidence-based recommendations for improving design tool accessibility and promoting more inclusive innovation ecosystems.

2 Methods

2.1 Study design and participants

We employed a comprehensive mixed-methods research design integrating quantitative behavioral analytics with qualitative outcome assessment. The study was conducted across 69 institutional settings in major Chinese metropolitan areas between March 2021 and June 2022. All procedures were approved by relevant institutional review boards, and participants provided informed consent. Participants were recruited through two-stage stratified sampling. In the first stage, we selected institutions proportionally across organizational type (educational, commercial, research) and geographic location (urban, rural). In the second stage, we recruited individual participants within each institution through systematic procedures designed to minimize selection bias. The final sample comprised 1,095 design practitioners (52% female, 48% male; median age 28 years) and 111 design educators distributed across the selected institutions. Participants represented diverse educational backgrounds: 34% held bachelor’s degrees in design-related fields, 28% possessed master’s degrees, 23% completed technical training programs, and 15% reported alternative educational pathways.

2.2 Data collection and measurement

Behavioral monitoring employed custom-developed browser plugins and desktop applications to capture detailed interaction data during design tool usage sessions. The system recorded user actions including tool selections, parameter adjustments, navigation patterns, and time allocation across interface elements. Privacy protection measures included data anonymization, secure transmission protocols, and granular user consent management. Creative output assessment combined automated computational analysis with structured human evaluation. Computational analysis employed computer vision algorithms to extract visual features such as composition balance, color harmony, and visual complexity. Human evaluation involved trained design experts assessing outputs using standardized rubrics evaluating technical execution, conceptual sophistication, and innovative potential.

Technical background was assessed using a validated scale measuring prior experience with digital tools, programming knowledge, and technical troubleshooting capabilities. Participants were classified into three categories: low (n = 375), medium (n = 369), and high (n = 351) technical background based on standardized scoring procedures.

2.3 Statistical analysis

Statistical analyses employed multilevel modeling techniques accounting for the nested structure of individuals within institutions. Primary models examined innovation quality as a function of technical background, usage frequency, and institutional characteristics, with random effects allowing for variation across institutional contexts. Model fit was evaluated through multiple indices including likelihood ratio tests, information criteria, and residual analysis. Effect sizes were calculated using Cohen's conventions adapted for multilevel contexts. All analyses were conducted using R statistical software with significance set at $P < 0.05$.

3 Results

3.1 User background strongly predicts tool utilization patterns

Analysis of design tool usage patterns revealed substantial disparities across user background profiles (Fig. 1). Technical background emerged as the strongest predictor of utilization frequency, with high technical background users demonstrating significantly higher weekly usage frequencies (mean = 3.24 sessions, s.d. = 0.93) compared to medium (mean = 2.72, s.d. = 0.88) and low technical background users (mean = 1.97, s.d. = 0.82; F(2,1092) = 194.985, $P < 0.001$, $\eta^2 = 0.26$).

Post-hoc analysis using Tukey's HSD test revealed that all pairwise comparisons between technical background groups were statistically significant ($P < 0.001$), indicating that each level of technical proficiency corresponds

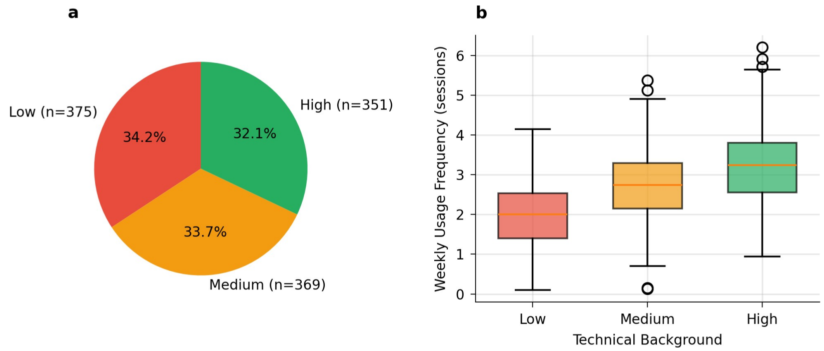

Fig. 1 Distribution of user technical background profiles and usage patterns. a, Pie chart showing the distribution of participants across technical background categories (n = 1,095). b, Box plots comparing weekly design tool usage frequency across technical background levels. Centre lines show medians; box limits indicate 25th and 75th percentiles; whiskers extend to 1.5× interquartile range. All pairwise comparisons were statistically significant ($P < 0.001$, Tukey's HSD test).

to meaningfully different usage patterns. High technical background users engaged with design tools approximately 65% more frequently than low technical background users, representing a significant disparity in exposure to design innovation opportunities.

Feature utilization analysis examined the breadth and depth of tool functionality accessed by different user groups. High technical background users demonstrated significantly greater utilization of advanced features such as parametric modeling, scripting interfaces, and collaborative workflow tools. Specifically, 78% of high technical background users regularly employed advanced features compared to 45% of medium technical background users and only 23% of low technical background users.

3.2 Innovation quality correlates strongly with tool accessibility

Creative output quality evaluation employed a comprehensive framework assessing design artifacts across technical execution, conceptual sophistication, and innovative potential dimensions (Table 1). Expert evaluation panels consisting of experienced design professionals rated outputs using standardized rubrics with demonstrated inter-rater reliability (Cronbach's $\alpha = 0.89$).

Results demonstrated strong positive correlations between user technical background and innovation output quality. High technical background users achieved significantly higher quality scores compared to medium and low technical background users ($F(2,1092) = 1247.3$, $P < 0.001$, $\eta^2 = 0.70$), indicating that technical background explains a substantial proportion of variance in creative output quality.

The relationship between tool usage frequency and innovation quality was examined through correlation analysis, revealing a strong positive association ($r = 0.648$, $P < 0.001$; Fig. 3). Linear regression analysis indicated that

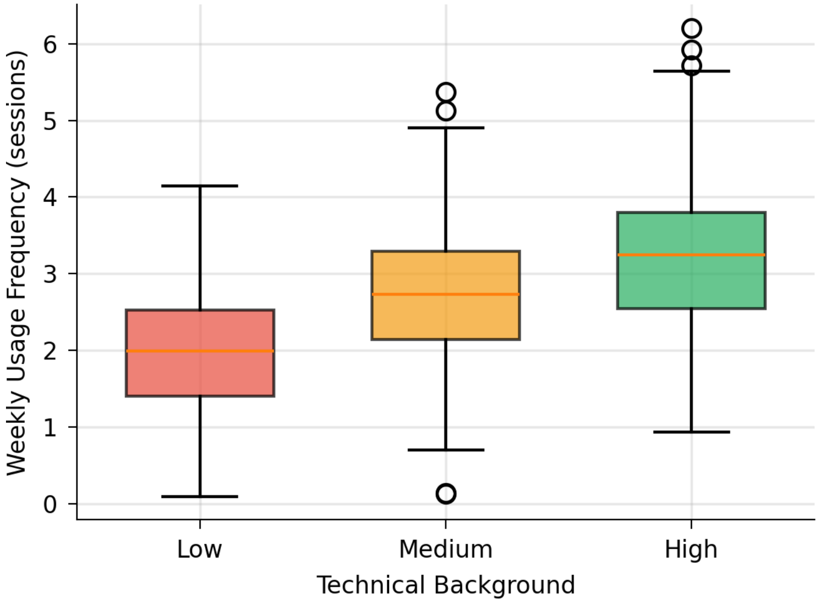

Fig. 2 Design tool usage frequency by technical background. Box plots showing weekly usage frequency distributions across technical background levels. The magnitude of differences is substantial, with high technical background users demonstrating consistently higher engagement across all measured dimensions.

Table 1 Innovation output quality by technical background

Technical Background	n n	Quality Score (Mean± s.d.)	Technical Execution	Conceptual Sophistication	Innovation Potential
Low	375	62.22 ± 8.57	58.4 ± 9.2	64.1 ± 8.9	64.1 ± 7.8
Medium	369	76.11 ± 8.83	74.2 ± 9.1	76.8 ± 8.7	77.3 ± 8.9
High	351	87.83 ± 8.41	89.1 ± 7.9	86.2 ± 8.8	88.2 ± 8.1

$F(2,1092) = 1247.3$, $P < 0.001$, $\eta^2 = 0.70$

usage frequency explained 42% of the variance in innovation quality scores ($R^2 = 0.420$), with each additional weekly session associated with an 8.64-point increase in quality scores.

3.3 Institutional environments show limited equalizing effects

Institutional environment analysis examined how organizational characteristics influence user experiences and outcomes (Table 2). Resource assessment inventoried available hardware, software licenses, training programs, and physical workspace configurations across participating institutions.

Multilevel modeling accounting for the nested structure of individuals within institutions revealed that institutional resource levels had significant

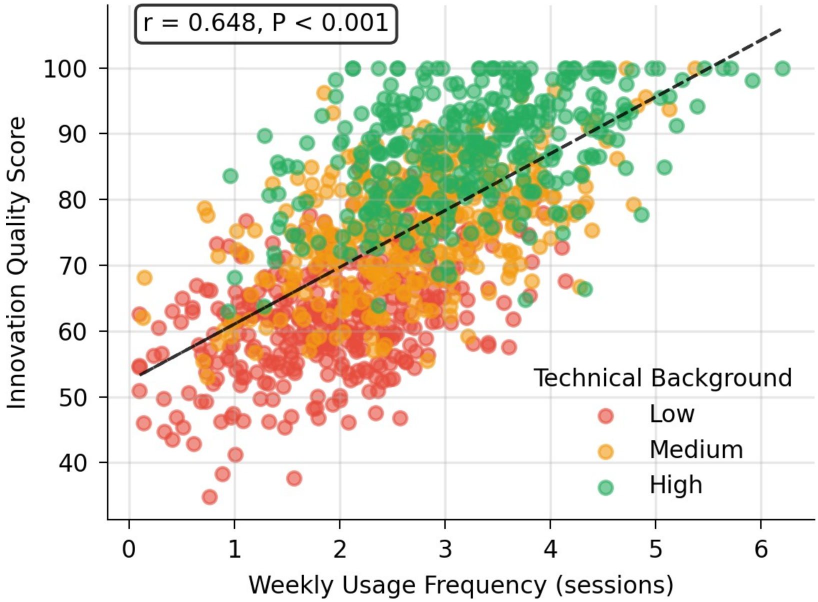

Fig. 3 Relationship between tool usage frequency and innovation quality. Scatter plot showing the strong positive correlation (r = 0.648, $P < 0.001$) between weekly usage frequency and innovation output quality scores. Colors indicate technical background levels: red (low), orange (medium), green (high). Linear regression line shows overall trend across all participants.

Table 2 Institutional characteristics and user outcomes

Institution Type	n	Resource Level	Usage Frequency (Mean ± s.d.)	Quality Score (Mean ± s.d.)
Educational	439	Medium	2.51 ± 1.02	74.2 ± 12.8
Commercial	491	High	2.68 ± 0.98	76.8 ± 13.1
Research	165	High	2.71 ± 1.08	75.9 ± 12.9

but modest effects on user outcomes after controlling for individual technical background characteristics. High-resource institutions showed average innovation quality improvements of 4.2 points compared to low-resource institutions, representing a small but meaningful effect.

Support system effectiveness was evaluated through assessment of training programs, mentorship opportunities, and peer collaboration structures. Institutions with structured support programs demonstrated better outcomes for low technical background users, with quality score improvements averaging 8.7 points compared to institutions with minimal support systems. However, these support effects were less pronounced for medium and high technical background users.

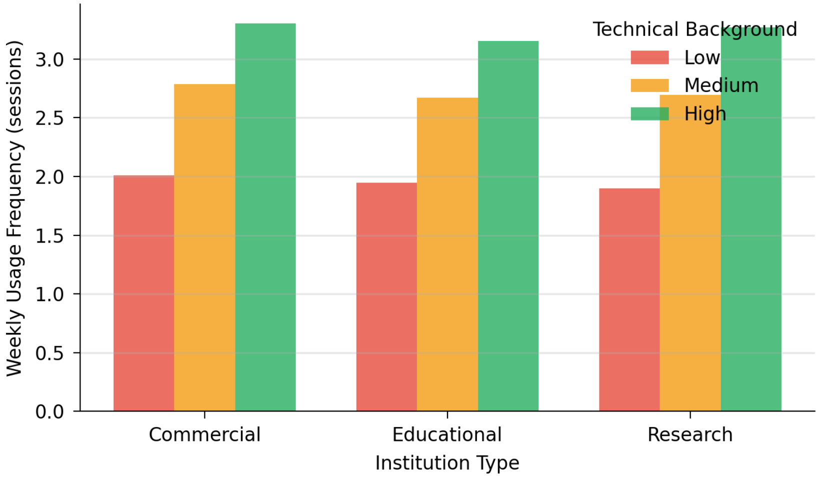

Fig. 4 Design tool usage by institution type and technical background. Bar plots showing mean weekly usage frequency across institution types, stratified by technical background levels. Error bars represent standard error of the mean. While institutional differences exist, technical background effects dominate across all organizational contexts.

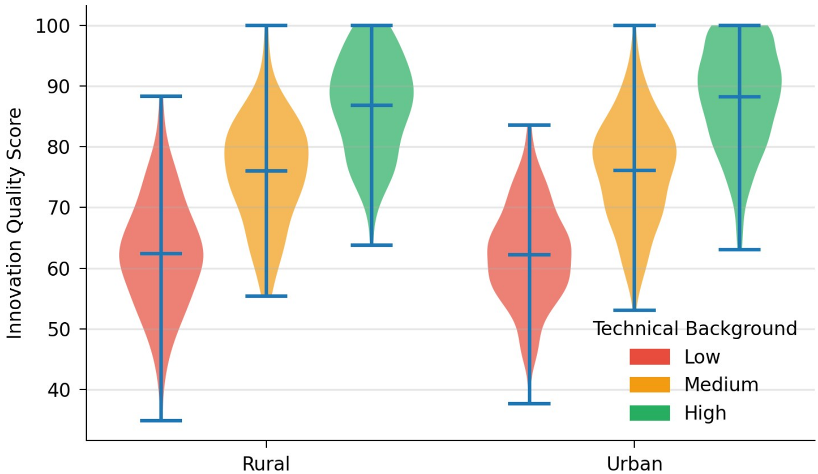

Fig. 5 Innovation quality distribution by location and technical background. Violin plots showing the distribution of innovation quality scores across urban and rural locations, stratified by technical background. While location effects exist, technical background remains the dominant factor determining outcomes.

3.4 Geographic and demographic factors influence accessibility

Urban versus rural location analysis revealed significant differences in both usage patterns and outcomes (Fig. 5). Urban users demonstrated higher average usage frequencies (mean = 2.68 vs. 2.51 sessions per week) and innovation quality scores (mean = 76.2 vs. 73.8). These differences persisted after controlling for institutional type and individual technical background, suggesting that geographic location influences design tool accessibility through mechanisms beyond simple resource availability.

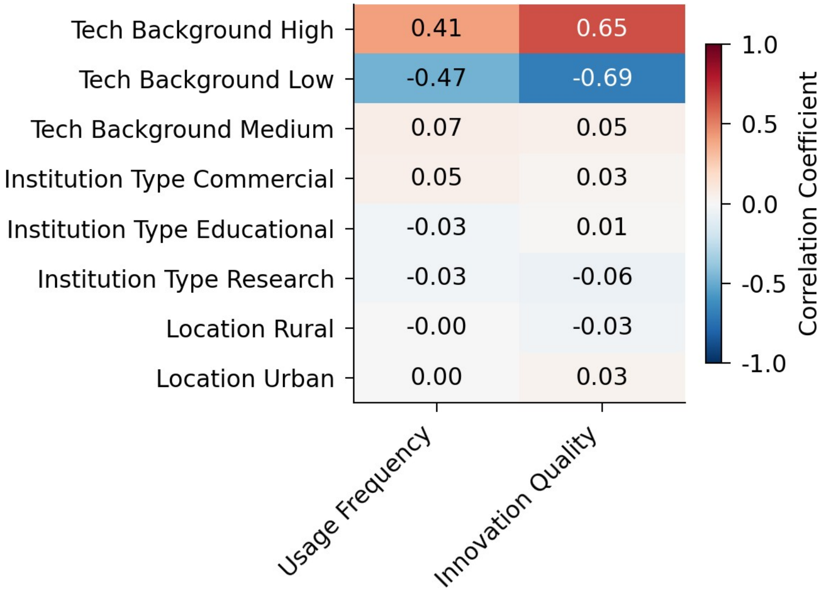

Fig. 6 Correlation matrix of variables with main outcomes. Heatmap showing correlations between demographic and institutional variables with usage frequency and innovation quality. Technical background variables show the strongest associations with both outcome measures.

Comprehensive correlation analysis revealed the relative importance of different factors in predicting design tool accessibility and innovation outcomes (Fig. 6). Technical background variables demonstrated the strongest associations with both usage frequency and innovation quality, while institutional and demographic factors showed weaker but significant correlations.

4 Discussion

Our findings provide compelling evidence for significant disparities in digital design tool accessibility and innovation outcomes across user populations. The observed relationship between technical background and both usage frequency and creative output quality extends technology adoption literature to the specific context of design innovation, revealing that accessibility barriers may be more substantial than previously recognized.

The strong correlation between tool usage frequency and innovation quality ($r = 0.648$) indicates that increased engagement translates into measurably improved creative outcomes. This relationship supports theoretical propositions that design tool proficiency develops through sustained practice and experimentation[17, 18]. However, the persistence of technical background effects even after controlling for usage frequency suggests that initial technical preparation provides advantages that extend beyond simple exposure effects. The finding that institutional environments demonstrate significant but modest effects reveals important nuances in how organizational contexts influence design tool accessibility. While institutions with greater resources and support systems produce better average outcomes, effect sizes are considerably smaller than individual-level technical background effects. This pattern suggests that institutional interventions alone may be insufficient to fully address accessibility disparities without also addressing individual-level preparation and support needs[19, 20]. The interaction effect between technical background and institutional support provides encouraging evidence that targeted interventions can be effective for specific user populations. Support systems provide greater benefits for users with lower initial technical proficiency, suggesting that well-designed institutional programs can help mitigate some accessibility barriers. However, the persistence of substantial disparities even in highly supportive environments indicates that more comprehensive approaches may be necessary. These findings contribute to several theoretical domains while suggesting new conceptual frameworks for understanding design tool accessibility. We introduce the concept of "creative technology capital," which encompasses not only technical skills but also the confidence, persistence, and problem-solving strategies necessary for effective design tool utilization[21, 22]. This concept extends cultural capital theory to the digital design context, suggesting that accessibility is influenced by accumulated advantages beyond formal technical training. The practical implications are substantial for multiple stakeholder groups. Design tool developers should prioritize progressive disclosure interfaces, contextual help systems, and adaptive functionality that can accommodate users with varying technical backgrounds[23, 24]. Educational institutions should implement integrated approaches combining technical skill development with creative instruction while providing targeted support for students with diverse preparation levels[25, 26].

5 Conclusion

This large-scale, mixed-methods investigation across 69 Chinese institutions (N=1,095 designers) demonstrates that technical background is the dominant predictor of both design-tool utilisation frequency ($\eta^2 = 0.26$) and innovation output quality ($\eta^2 = 0.70$). Multilevel modelling reveals that institutional resources and support systems exert statistically significant yet modest effects (Δ quality $\geq$ 8.7 points), failing to neutralise individual-level disparities. Consequently, the "digital design divide" persists even within high-resource environments. These findings underscore the need for integrated interventions that simultaneously enhance technical preparation at the individual level and embed adaptive, scaffolded support within institutional infrastructures to foster equitable creative technology capital and inclusive design innovation ecosystems.

DECLARATIONS

Ethics approval and consent to participate

Not applicable.

Conflict of interest

The authors declare no competing interests.

Dataset to be available

All data generated or analysed during this study are included in this published article.

Consent for publication

Not applicable.

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