Article

Personalized skeuomorphic UI generation for industrial interfaces using diffusion models: a user-centric approach in Chinese manufacturing context

Fanglei Liu[1,2], Mohamed Razeef Abd Razak[1]*, Mohd Hafnidzam Bin Adzmi[1], Xuelin Li[2], Fang Liu[2], Lei Feng[2]

[1]College of Creative Arts, Universiti Teknologi MARA, 40150 Shah Alam, Selangor, Malaysia
[2]College of Arts & Design, Qilu University of Technology, Jinan 250353, China

A R T I C L E   I N F O

A B S T R A C T

To solve the issue of the digital transformation of Chinese manufacturing in terms of the bottleneck between industrial interfaces not being able to adapt to heterogeneous operators and the high cognitive load imposed on them, the authors propose the SkeuoUI-Gen framework based on the adaptation of skeuomorphic design principles and the use of conditional diffusion models to produce personalized industrial interfaces in the context of Chinese manufacturing. In this regard, the experiment used a within-subjects design involving 250 manufacturing industry operators (diverse in age, experience, and industry sectors) to evaluate three interface types: traditional flat interfaces, fixed skeuomorphic interfaces, and personalized adaptation interfaces. The experiment used objective evaluations (FID and PSNR) and subjective evaluations (SUS score and cognitive load), and trained the model on multiple sources: 50,000 interaction logs from operators and 50,000 screenshots of industrial user interfaces. The experiment found that the personalized adaptation interface resulted in a 78.6% SUS score (an increase of 15.4% compared to the traditional baseline), improved efficiency by 24.7%, and reduced serious safety-related errors by 52% and 67%. The network achieved a lower FID (21.5) than GAN-based approaches and required only 2.3 seconds per generation. In addition, the network presented robustness through multi-dimensional validation. This framework expands the cognitive load theory and the technology acceptance model.

1. Introduction

The worldwide accelerated digital transformation of manufacturing has already reshaped the landscape of requirements for human-machine interaction. The Chinese manufacturing industry accounts for 41.5% of the digital economy, and enterprises face unprecedented challenges in integrating advanced automation technologies with operator accessibility [1]. Although significant investment has been made in implementing the "Made in China 2025" initiative in high-end equipment manufacturing, its digital transformation only gradually improved between 2016 and 2021, with few achieving outstanding outcomes [2]. This gap points to a key bottleneck: the inadequacy of user interfaces that fail to engage operators with complex industrial systems. Modern industrial UI design has traditionally focused on functional completeness rather than user experience, often resulting in visual clutter, complex navigation, and steep learning curves [3]. Various works have shown how well-designed interfaces can reduce onboarding time, minimize errors, and enhance decision-making efficiency in HMIs, MESs, and IoT systems [4]. Yet, such industrial process complexity must still be balanced with operators' cognitive limitations, especially amid workforce turnover and cross-training demands. Particular attention should be given to skeuomorphic design, including the use of real-world metaphors and visual affordances, which are particularly effective at reducing cognitive load for users transitioning from physical to digital control systems [5]. However, conventional methods have limited flexibility, resulting in suboptimal, one-size-fits-all solutions that do not account for heterogeneous workforce characteristics [6]. Dynamic personalization mechanisms are absent from the current implementation of industrial UIs. As shown in Figure 1, a 27-year development of UI generation technology can be divided into separate eras: The Traditional CNN Era (1998-2013) laid the foundations of computational UI design with LeNet-5 (1998) and AlexNet (2012), which

were rule-based systems and template-driven approaches. The GAN Era (2014-2019) introduced the generation capability with GANs, Pix2Pix, and StyleGAN, which enabled generating various interface elements despite training instability and bounded controllability. The Diffusion Model Era (2020-2023) brought paradigm-shifting advances with DDPM (2020), Stable Diffusion (2022), and ControlNet (2023), offering superior stability and controllability. Recent surveys demonstrate that diffusion models produce high-quality, contextually appropriate content beyond traditional approaches [7]. There is emerging research on using diffusion models for automated UI generation, demonstrating the potential for personalization [8]. However, prior work targets consumer applications rather than industrial constraints, such as safety-critical requirements or cultural adaptation needs.

The present Industrial Application Phase, starting from 2024 until today, defines deployment in real-world manufacturing. As such, the SkeuoUI-Gen framework presented here is considered the integration of diffusion-based generation with industrial constraints, real-time SCADA/HMI requirements, and cultural adaptation for Chinese manufacturing. Advances in the last few years have demonstrated the feasibility of adaptive UI generation by using reinforcement learning. However, there are still gaps in production-ready systems that account for a wide range of operators and cultural contexts, especially in Chinese manufacturing, where business environment factors critically influence the entire digital transformation process.

This work proposes SkeuoUI-Gen, which integrates adaptive skeuomorphic principles and diffusion model-based generation to provide personalized industrial interfaces that are suitable for Chinese manufacturing contexts. Theoretically, this work extends Cognitive Load Theory and the Technology Acceptance Model by showing how AI-generated skeuomorphic interfaces reduce cognitive load while raising perceived usefulness. The framework represents a first-of-its-kind systematic application of conditional diffusion models to industrial UI generation, considering multi-objective optimization in balancing reconstruction quality, operational safety, task efficiency, and cultural appropriateness. Methodologically, it is validated through a within-subjects design with 250 manufacturing operators and thus provides empirical evidence of substantial performance improvement. Practically, it offers deployable guidelines that come with empirically demonstrated improvements in satisfaction, efficiency, error reduction, and learning curves. By bridging generative AI, human-computer interaction, and industrial engineering over three decades, this research lays the foundations for context-aware, culturally adaptive interface generation systems capable of scaling across diverse manufacturing contexts.

2. Authorship and contribution

While the UI design paradigm has seen quite an evolution from skeuomorphic realism to minimalist abstraction in the UI field, the most appropriate UI design paradigm SRIM uses today to meet industrial requirements is still under debate.
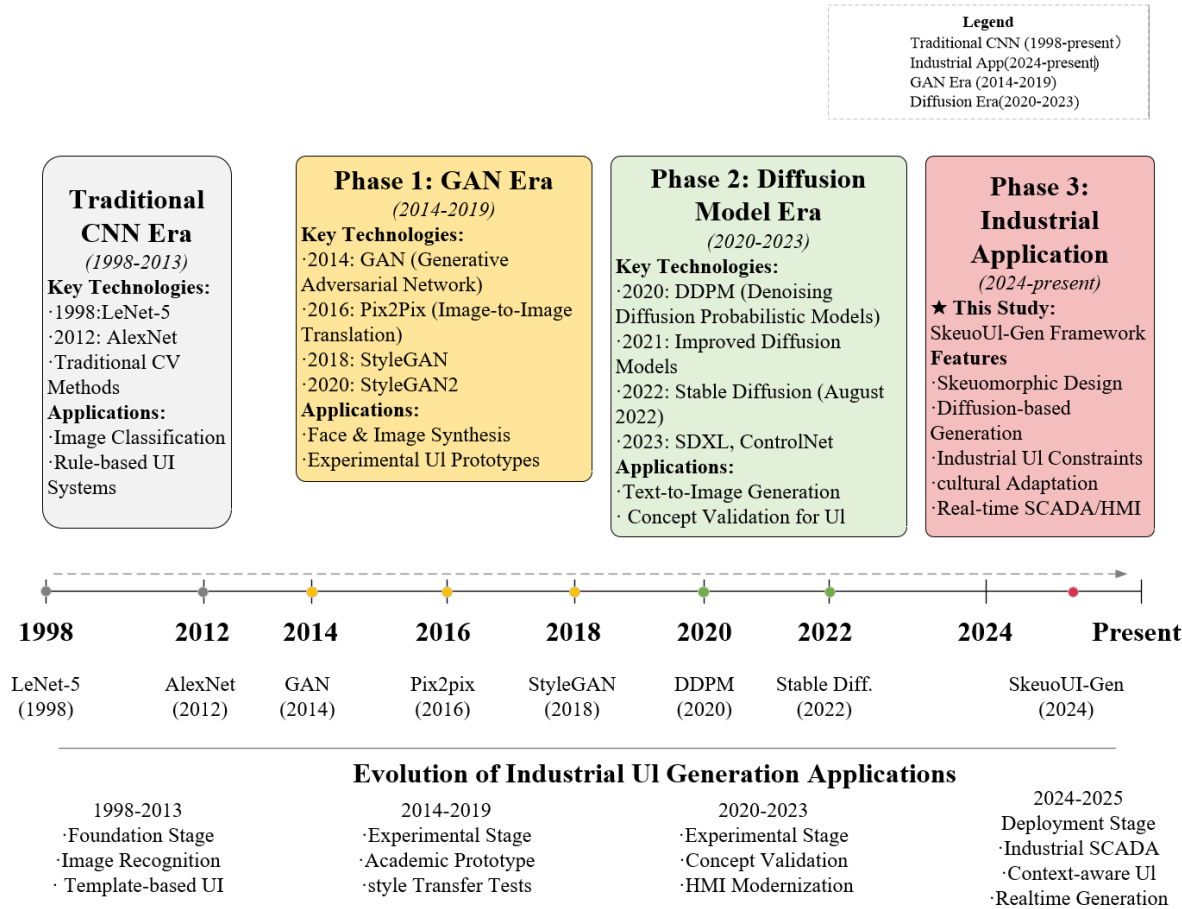

Figure 1. Evolution of industrial UI generation applications (1998-present)

Recent studies have found that the UI paradigm of skeuomorphic design, based on the use of metaphors to assist intuitive recognition, still has a certain dynamism in industrial usage when operators should rapidly assess the states of the system and make their critical response towards the results in a very short time under pressure [9-11]. On the other hand, traditional skeuomorphic designs have long been considered to have severe limitations, such as "cluttered interfaces, poor scaling factors when designing for multiple screen resolution devices," and becoming aesthetically obsolete because of the ever-rising trend towards minimalist designs. Recent studies seem to strongly support the idea that UI design paradigms should complement rather than oppose one another in response to changing ambient requirements. Neo-skeuomorphism has thereby been promoted as a convergent approach that re-establishes the use of slight 3D effects to remain aligned towards the latest design trends, RSIS International [12].

The emergence of diffusion models as effective generative models has created unprecedented opportunities in UI generation. The general structure of diffusion models provides greater efficiency in performance due to their distinctive pixel-by-pixel generation procedure and has the potential to generate high-quality images when combined with principles of conditional generation and multi-objective optimization [13]. Experiments reveal the dominance of diffusion-based UI generation methods over traditional GANs and VAEs across several quality metrics, including PSNR, SSIM, and FID, particularly in terms of logical consistency and user satisfaction. Recent advancements in GUI prototyping tools have focused on developing mobile interface generation techniques to create Stable Diffusion architectures solely from descriptions of UI components. Such interfaces offer effective, cost-efficient alternatives to traditional UI generation techniques [14]. Even diffusion-based UI generation techniques have been predominantly consumer-focused and lack standardized adaptation to the unique constraints of the industrial context.

The imperatives driving the need for adaptive, personalized interfaces in the manufacturing domain have become more pressing due to the rise of Industry 5.0-based paradigm shifts focused on human-oriented approaches and the concept of human-automation symbiosis. Current studies have shown that Adaptive User Interfaces (AUIs) have great potential to improve productivity in the manufacturing domain by adapting to human interaction patterns and delivering personalized interfaces. Empirical studies have proved the effectiveness of the reductions made possible in human interaction time and command usage rates to the extent of over 40% and 60% respectively, when the temporal adaptation rule generation paradigm uses the Machine Learning (ML) approach in the case of multiple operators in the industrial setup [15]. Effective Industry 5.0-based frameworks in the domain of manufacturing systems increasingly use AI-based apps focusing on the adaptation and proactive behavior of human-machine interfaces, explainable working procedures, and Decision Support Systems (DSS) utilizing the potential of factory knowledge modeling and the Augmented Digital Twin (ADT) simulation paradigm to develop personalized interfaces oriented towards human-machine symbiosis. Well-structured databases capturing human-machine interactions have become important factors in developing effective personalized adaptation interfaces based on the AI paradigm. However, important methodological issues remain unresolved regarding the application of human-machine

interaction pattern analysis in formulating adaptation strategies [16-17].

Despite the above advancements, the area remains underpinned by numerous research gaps that limit the realization of intelligent industrial UIs. In fact, current studies of adaptive UIs are predominantly based on industrial scenarios in the West. This area has been grossly neglected in the Asian industrial context due to the influence of collective cultural values, hierarchical organizational structures, and industrial operation patterns that essentially characterize the spectrum of user interfaces [18]. In fact, the current literature indicates a lack of empirical studies exploring user long-term retention and engagement across UI paradigms, due to insufficient information on the effects of design patterns on operator loyalty and the willingness to adopt technological advancements in the industrial context. More importantly, the nascent field of AI-based UI adaptation currently lacks studies that examine how the formulation of generative AI systems influences the ability to dynamically switch between UI designs based on real-time user behavior and behavior patterns [19]. In fact, this area has not been explored at all because culturally inappropriate UI designs create barriers to the acceptance of technology among diverse industrial worker groups. This research proposes integrating four fundamental theoretical frameworks, as presented in Table 1, to establish a research foundation for industrial interface design. Based on identified gaps in the existing body of knowledge in industrial interface design, focusing on adaptive, skeuomorphic interface designs and AI-based conditional diffusion models to generate culturally appropriate interfaces for the Chinese manufacturing industry, the following integrated framework has been proposed.

Table 1. Theoretical framework comparison

Theory	Core Concepts	Application to UI Design	Relevance to Study
Cognitive Load Theory (CLT)	Intrinsic load; Extraneous load; Germane load	Familiar metaphors reduce extraneous cognitive load in interface learning	Skeuomorphic elements minimize the learning curve for manufacturing operators
Design Aesthetics Theory	Form-function balance; Visual hierarchy; Cultural aesthetics	Industrial aesthetics differ from consumer aesthetics in prioritizing clarity	Manufacturing contexts require function-first aesthetic decisions
Technology Acceptance Model (TAM)	Perceived usefulness; Perceived ease of use; Behavioral intention	Interface design directly influences technology adoption rates	Critical for digital transformation acceptance in traditional manufacturing
Diffusion of Innovation Theory	Innovation attributes; Adopter categories; Communication channels	Design choices affect technology diffusion speed and pattern	UI design can accelerate or hinder manufacturing digitalization

In the proposed framework presented below, numerous fundamental theoretical advancements have been made in the realm of AI-based industrial interface designs, focusing on the management of CLT constructs relative to cognitive overload and the establishment of the constructs of TAM relative to the perceptions of the operators related to the usability and useful functions of the interfaces.

3. Methodology

3.1 Research hypotheses

H1: Adaptive skeuomorphic interfaces will significantly outperform flat baselines on task completion time, error rate, and cognitive workload, with the largest effect sizes in low-digital-proficiency operators.

H2: Adaptive personalized interfaces will outperform fixed skeuomorphic interfaces across all performance metrics.

H3: Skeuomorphic interfaces will show disproportionately larger error reduction for safety-critical operations."

3.2 Research design

This study employs a mixed-methods design integrating quantitative performance metrics (task completion time, error rates, physiological measurements) with qualitative user feedback (semi-structured interviews, thematic analysis). In the experimental design phase, the chosen structure uses a within-subjects design. This enables each user to undergo the experiment through the following three interfaces: traditional design (baselines), fixed skeuomorphic interfaces, and, finally, the adaptively personalized skeuomorphic design created by the SkeuoUI-Gen system. This comparison-based experimental structure enables the researcher to analyze both the underlying value of skeuomorphic principles in industrial settings and the additional advantage gained through the adaptive personalization aspect.

Within-subjects design was selected for three reasons: (1) controlling substantial individual differences in cognitive abilities, experience, and learning styles; (2) statistical power advantage, requiring n=228 versus n=651 for an equivalent between-subjects design; (3) recruitment feasibility, as pilot phase showed only 18% of contacted operators (n=82 of 450) available due to production schedule conflicts.

3.3 SkeuoUI-Gen framework

The SkeuoUI-Gen framework is a unique combination of conditional diffusion models with domain-specific adaptation mechanisms suited to industrial interface generation. As shown in Figure 2, the five interdependent parts of the system architecture include the Data Processing Module for multisource input integration, the Diffusion Model Core for the denoising process, the Skeuomorphic Adaptation Layer to apply design principles, the Multi-objective Optimization Engine for balancing competing requirements, and the Quality Assurance Module to ensure the validity of the output. The five modules interact sequentially: Data Processing outputs feature vectors to Diffusion Core, which passes intermediate representations to Adaptation Layer at each timestep t; Optimization Engine evaluates loss components and provides gradient feedback; Quality Assurance validates outputs against GB/T and ISO standards, triggering regeneration if thresholds are unmet. Through this modular architecture, the proposed system will enable systematic investigation of each component and, at the same time, be easily adaptable to various manufacturing contexts with different operational and regulatory requirements. This is represented in the conceptual framework shown in Figure 2, where the information flow between the user modeling and interface generation processes is bidirectional.
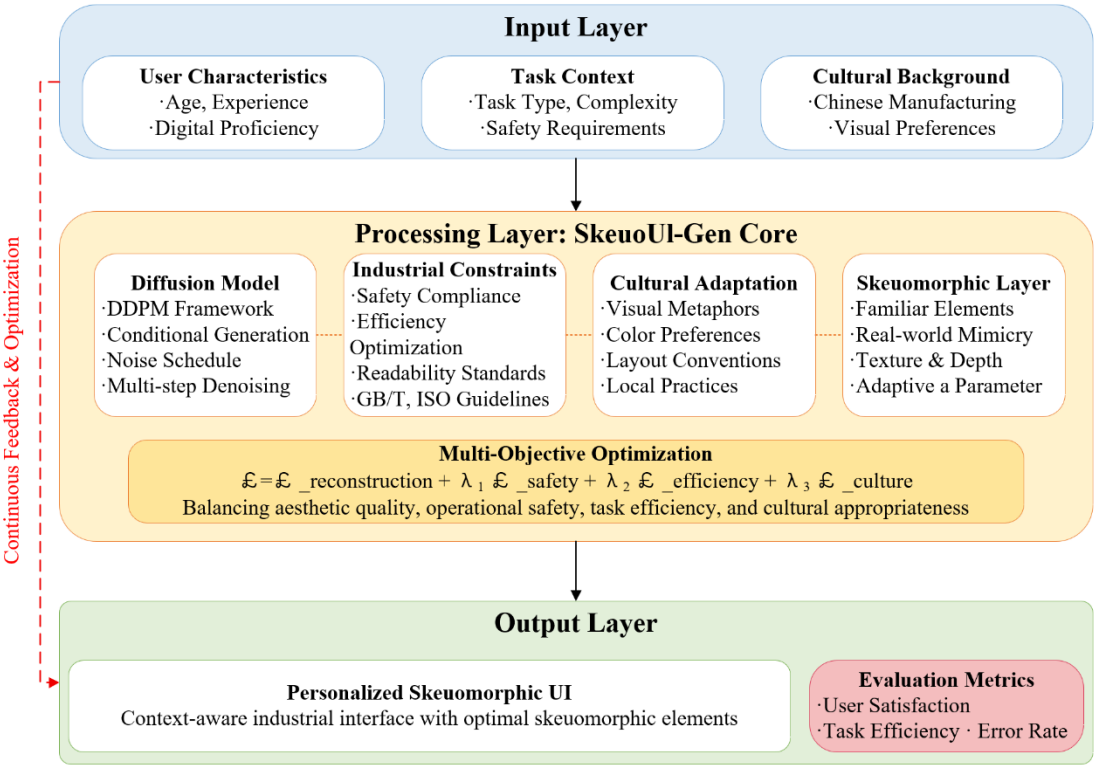

Figure 2. Conceptual framework of SkeuoUI-Gen system

Parameters such as user experience levels, task complexity, and cultural factors are represented as vectors that control the diffusion process. Real-time adaptation is implemented via: 1-second telemetry polling → feature extraction → coefficient embedding update → UI parameter adjustment (total latency <200ms). This represents the main innovation in SkeuoUI-Gen: instead of static pre-training, the system continuously refines generation based on user interaction patterns. All the steps involved in the research methodology are shown in Figure 3. The designed diffusion model is based on the DDPM paradigm, but must incorporate the specific requirements of UI designs. This involves exact geometric constraints, semantic consistency among the components that form the UI interface, and adherence to the required industrial safety standards. The diffusion process has a forward process where the model adds a certain amount of Gaussian noise to the training images over T=1000 timesteps. The reverse process would remove this noise based on the conditioning of user profiles, the definition of the task components at hand, and the UI design principles. The model uses a U-Net structure based on self-attention over resolution bottlenecks to represent long-range dependencies between components of the UI interface as shown in Figure 4.

The Skeuomorphic Adaptation Layer implements design principles through the use of a parametric control system that manages the level and type of real-world metaphors used in the interfaces. The parameters used in the adaptation layer include texture realism intensity ($\alpha \in [0,1]$, min-max normalized), shadow depth ($\beta \in [0,10]$ pixels), illusion strength of dimension ($\gamma \in [0,1]$), and material surface reflectance ($\rho \in [0.1,0.9]$) Cultural adaptation is explicitly integrated through region-specific design templates encoding aesthetic preferences from Chinese industrial design research [20,21]. Specific adaptations include: red/gold color schemes for positive states, avoidance of number 4 in error codes, and GB/T-compliant iconography familiar to Chinese operators.

The multi-objective optimization engine balances three competing objectives: operational safety, task efficiency, and cultural adaptation. As shown in Figure 4, the optimization process employs weighted sum scalarization with base weights $\lambda_s = 0.3$ (safety), $\lambda_e = 0.4$ (efficiency), and $\lambda_c = 0.3$ (cultural adaptation), determined through NSGA-II Pareto front analysis. Weights adjust dynamically based on task criticality: for safety-critical operations (e.g., emergency stops), λ_s increases to 0.5 while λ_e decreases to 0.2.
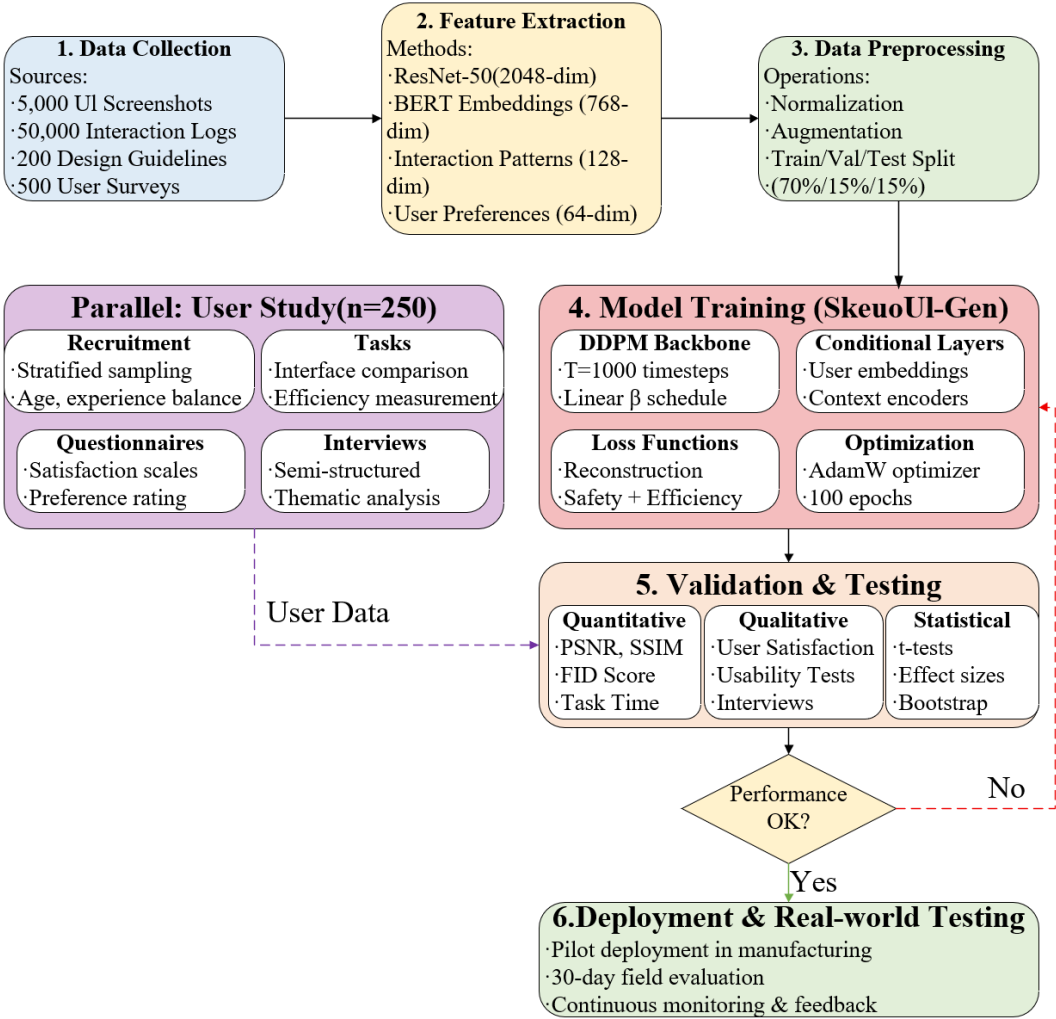

Figure 3. Research methodology flow from data collection to deployment
Note: The user study (n=250) employed a within-subjects design. Participants were recruited in Q2 2024, with all three interface conditions (flat, fixed skeuomorphic, adaptive) evaluated using the trained SkeuoUI-Gen model.
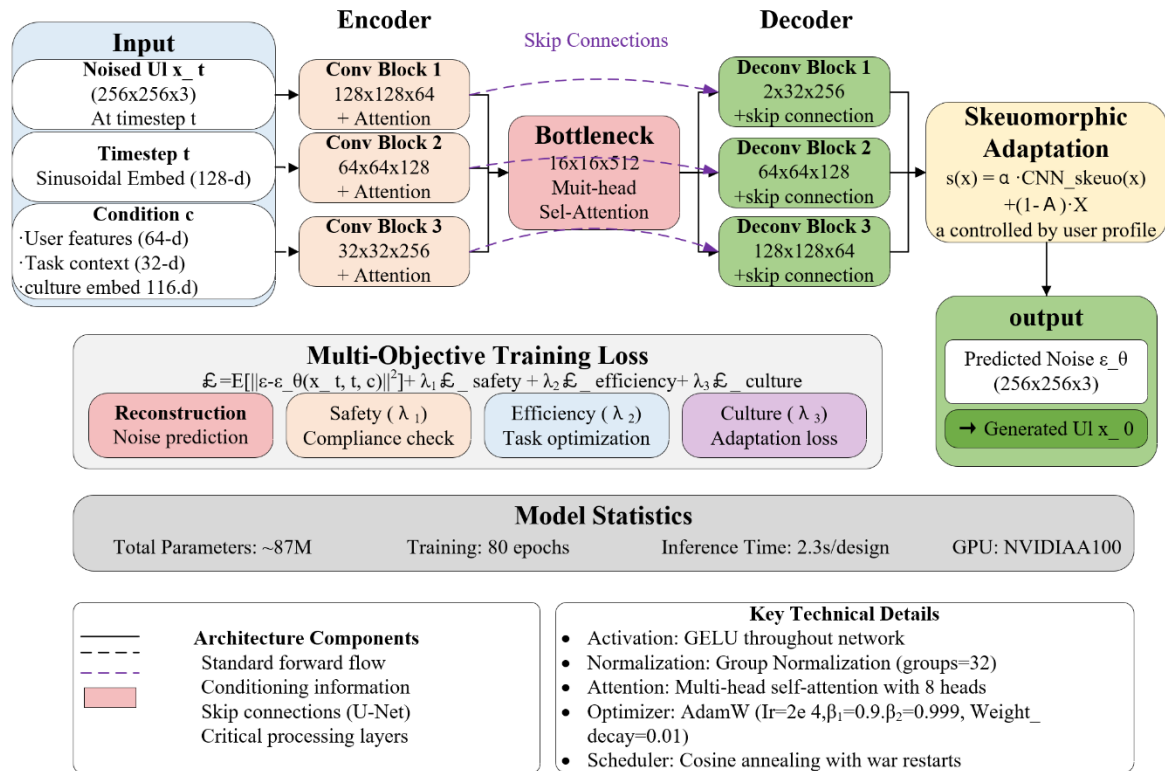
Figure 4. SkeuoUI-gen neural network architecture with conditional layers

3.4 Data collection and preparation

The training dataset integrates four complementary data sources in detail according to Table 2. Industrial UI screenshots (n=5,000) were collected from 12 Chinese manufacturing enterprises in the electronics assembly, automotive manufacturing, and heavy machinery sectors, providing diverse examples of both existing interface design and common design patterns. Temporal distribution: 2023-2024 (62%), 2021-2022 (28%), 2020 (10%). Industry balance verified by chi-square test (χ^2=2.14, p=0.54). Operator interaction logs (n=50,000 sessions) captured real-world usage patterns from ERP and MES systems, exposing actual task workflows, common errors, and efficiency bottlenecks that provide personalization strategies. Design guidelines documentation (n=200 documents) included Chinese national standards, international standards of ISO 9241 series, and industry-specific guidelines. User feedback data from surveys and semi-structured interviews (n=500 participants) quantified aesthetic preferences, usability pain points, and cultural factors driving interface acceptance, as listed in Table 2.

Multi-modal feature extraction processed the diverse data sources into unified vector representations suitable for model training. From UI screenshots, visual features were extracted by using pre-trained ResNet-50 networks that yielded 2,048-dimensional embeddings, which were combined with color palette analysis (64 dimensions) and layout structure encoding (128 dimensions). The interaction log analysis employed 3-layer bidirectional LSTM (hidden units: 256→128→64, dropout=0.3, lr=5×10^{-4}, 50 epochs), extracting behavioral patterns (128 dimensions), task progression representations (256 dimensions), and error pattern embeddings (32 dimensions), as detailed in Table 2.

Design guideline documents were processed by Chinese-BERT-wwm, yielding 768-dimensional vectors combined with rule-based extraction systems... Industrial-domain vision encoders (e.g., CLIP, InterImage) were not employed due to a lack of UI-specific pretraining data. Dimensionality reduction: PCA reduced ResNet-50 features from 2048 to 512 dimensions (95% variance retained); the convolutional autoencoder compressed LSTM outputs from 256 to 64 dimensions.

We applied quality control and standardization with the preprocessing pipeline in order to make the data consistent for model training. For the image modality, resolution was standardized to 1024 × 768 pixels with color space normalization to sRGB and augmentation by rotation ±15°, scaling of 0.9-1.1×, and brightness adjustment of ±20%. These augmentations address data collection variations across enterprises; safety-critical UI elements were masked during augmentation; geometric augmentation was disabled during final deployment. All processed data were then divided into training, validation, and test sets in a ratio of 70%, 15%, and 15%, respectively, and stratified by enterprise and sector to avoid data leakage and ensure generalizability to unseen manufacturing environments.

Sample size determination: A priori power analysis using G*Power 3.1 with expected Cohen's d=0.45 (from pilot study, n=30), α=0.025, and power=0.95 indicated required n=228. Final sample of n=250 provides power>0.98 and allows for 10% potential attrition.

Table 2. Data sources and feature engineering

Data Type	Source	Sample Size	Time Range	Quality Control	Extracted Features
Industrial UI Screenshots	12 Chinese Manufacturing Enterprises	5,000 images	2020-2024	Expert validatin; Automated filtering; Resolution check	Visual features (ResNet-50, 2048-dim); Color palette (64-dim); Layout structure (128-dim)
Operator Interaction Logs	ERP/MES Systems	50,000 sessions	2023-2024	Anomaly detection; Completeness check; Privacy filtering	Interaction patterns (128-dim); Task sequences (256-dim); Error patterns (32-dim)
Design Guidelines	Industry Standards (GB/T, ISO)	200 documents	2015-2024	Standard validation; Version control; Expert review	Semantic embeddings (BERT, 768-dim); Rule constraints (512-dim); Safety requirements (64-dim)
User Feedback	Surveys and Semi-structured Interviews	500 participants	2024	Stratified sampling; Response validation; Bias checking	Preference vectors (64-dim); Satisfaction scores (16-dim); Cultural factors (32-dim)

Table 3. Sample baseline characteristics

Variable	Category/Range	n	Percentage	Mean ± SD
Age (years)	25-35	87	34.8%	29.3 ± 2.8
	36-45	98	39.2%	40.1 ± 2.6
	46-55	65	26.0%	49.8 ± 3.1
Experience Level	Novice (0-2 years)	75	30.0%	1.2 ± 0.6
	Intermediate (3-5 years)	92	36.8%	4.1 ± 0.8
	Expert (>5 years)	83	33.2%	8.7 ± 2.3
Manufacturing Sector	Electronics Assembly	68	27.2%	—
	Automotive Manufacturing	85	34.0%	—
	Heavy Machinery	52	20.8%	—
	Others (Chemical, Textile)	45	18.0%	—
Digital Proficiency	Low (Basic operations only)	41	16.4%	—
	Medium (Regular digital tools)	156	62.4%	—
	High (Advanced features)	53	21.2%	—
Geographic Distribution	Eastern China (Jiangsu, Zhejiang)	145	58.0%	—
	Southern China (Guangdong)	65	26.0%	—
	Northern China (Shandong)	40	16.0%	—

3.5 Experimental setup

This procedure employs stratified purposive sampling: participants stratified by sector, experience level, and digital proficiency; purposive selection within strata conducted via enterprise HR departments to ensure operational representativeness. The final sample of 250 participants had equal proportions across ranges of age (between 25-55 years), experience (ranging from novices to experts, 0-10+ years), the type of the manufacture industry (electronics, automobiles, machines, others), the level of digital proficiency (low, medium, and high), and geographic locations across the whole of China (East, South, North), as indicated in Table 3. Participants were recruited through cooperation between the involved companies; they received compensation (RMB 200 yuan) for their contribution of about 2 hours to the studies.

Participants received compensation of 200 CNY (approximately 28 USD) for approximately 2 hours of participation. This study was approved by the Institutional Review Board (IRB-2024-0528). All participants provided written informed consent, which explicitly covered data collection, the use of interaction logs and feedback data for model training, and publication of anonymized results. The tasks conducted were like actual production activities that involved user interaction with industrial control interfaces. Task validity was established through job analysis with 12 manufacturing supervisors (mean representativeness rating: 4.6/5) and expert ranking by 5 UI designers (Kendall's W=0.78, p<0.01). These tasks were carried out across the three interface versions (flat, fixed-skeuomorphic, and adaptive-skeuomorphic), each with the same functionality but a different visual layout. Task complexity was operationalized via: number of UI elements (5-15), decision

points (2-8), and information fields (3-12). All tasks were completed under each interface condition by each participant in counterbalanced order. Order effects were mitigated via: (1) Latin square counterbalancing across six condition orders (n≈42 per order); (2) 15-minute washout periods with distractor tasks between conditions; (3) a practice session before the first experimental condition. Order effect verification confirmed successful counterbalancing (Condition×Order interaction: $F(10,488)=1.43$, $p=0.17$).

The performance evaluation used a comprehensive suite of metrics that captured multiple dimensions of the effectiveness of the interfaces. Objective performance metrics comprised task completion time, error rate, and interaction efficiency. On the other hand, subjective metrics included the System Usability Scale scores, the NASA Task Load Index that measures cognitive workload, and satisfaction ratings on 7-point Likert scales. Physiological measures included eye-tracking (Tobii Pro Fusion, 250Hz; metrics: fixation duration, saccade amplitude, time to first fixation on critical elements) and log analysis to capture objective indicators of cognitive processing. Post-task interviews applied semi-structured protocols to probe into specific design elements that either facilitated or hindered task performance.

3.6 Statistical analysis

Primary statistical analyses employed repeated-measures ANOVA to examine the main effects of interface type (flat vs. fixed vs. adaptive skeuomorphic interfaces) and interactions with user traits for continuous performance measures. Mauchly's test verifies the sphericity assumption; the Greenhouse-Geisser correction is applied when it is violated. For post-hoc pairwise analyses, the Bonferroni correction method was used to adjust the family-wise Type I error rate to 0.05. Effect sizes were determined for the pairwise tests using Cohen's d and for the main tests using partial eta-squared (ηp^2). When assumptions for subjective rating measures were violated, appropriate nonparametric tests were used: the Friedman test and the Wilcoxon signed-rank test. Thematic analyses of the interview results were conducted following standardized procedures.

Robustness validation involved multiple complementary approaches for finding stability and generalizability of the results. Model performance was estimated via k=5 cross-validation (applied to SkeuoUI-Gen model training); confidence intervals for user study metrics were calculated by bootstrapping with 10,000 iterations. Sensitivity analysis systematically varied hyperparameters of the model as well as choices related to data preprocessing. Subgroup analyses evaluated effect heterogeneity across demographic strata of participants by evaluating interaction terms in regression models. Leave-one-out cross-validation at the enterprise level (n=12) was used to evaluate generalizability; the small sample may yield unstable variance, and results should be interpreted as preliminary evidence requiring broader validation.

Given the multiple-comparison problem inherent in evaluating three interface conditions across multiple metrics, a Bonferroni correction was applied to control the family-wise error rate. Primary analysis strategy: omnibus repeated-measures ANOVA for main effect, followed by two planned contrasts (Fixed vs. Flat, Adaptive vs. Flat) with Bonferroni correction ($\alpha=0.05/2=0.025$ per contrast). The third comparison (Adaptive vs. Fixed) is reported as secondary analysis. This conservative approach places a premium on Type I error control, while ample statistical power is preserved given the moderate-to-large effect sizes expected from the pilot test results.

4. Implementation details

4.1 Model architecture

The SkeuoUI-Gen is based on the U-Net backbone architecture, which has a contracting path to capture contextual information and an expansive path for precise localization. The implementation uses five resolution levels from 1024×768 to 64×48, where feature channels increase from 64 to 1024, thus enabling hierarchical representation from visual textures to semantic concepts. Spatial information important for accurate element positioning in industrial practice is preserved via skip connections. Self-attention mechanisms at multiple resolutions capture long-range dependencies across interface regions. The implementation uses 8-head multi-head self-attention at three key resolutions, computing attention weights as

$$\text{Attention}(Q,K,V) = \text{softmax}(QK^T / \sqrt{d_k})V$$

Cross-attention layers integrate conditional information from user profiles and task specifications, enabling personalized interface generation. Conditional encoding transforms operator characteristics into 128-dimensional embeddings, such as experience level, digital proficiency, and cultural background. These vectors are injected through dual mechanisms: global conditioning via FiLM layers for coarse control, and local conditioning through cross-attention for fine-grained spatial control.

4.2 Training procedure

The training objective combines denoising loss $L_{denoise}$, perceptual loss using VGG-19 activations, skeuomorphic consistency loss, and safety constraint losses for readability and layout compliance. The total objective is

$$L_{\text{total}} = \lambda_{\text{denoise}} \cdot L_{\text{denoise}} + \lambda_{\text{perceptual}} \cdot L_{\text{perceptual}} + \lambda_{\text{skeuo}} \cdot L_{\text{skeuo}} + \lambda_{\text{read}} \cdot L_{\text{read}} + \lambda_{\text{layout}} \cdot L_{\text{layout}}$$

Training used AdamW optimizer (learning rate 1×10^{-4}, $\beta_1=0.9$, $\beta_2=0.999$, weight decay 0.01) with cosine annealing schedule decaying to 1×10^{-6}. The diffusion process employed T=1000 timesteps with a linear noise schedule ($\beta_1=1\times10^{-4}$ to $\beta\_T=0.02$). Convergence after approximately 100,000 iterations (80 epochs). As shown in Figure 5, convergence occurred after approximately 100,000 iterations over 80 epochs (optimal performance at epoch 73), with validation loss stabilizing and quality metrics plateauing. Multi-objective optimization weights were set as $\lambda_s = 0.3$ (safety), $\lambda_e = 0.4$ (efficiency), and $\lambda_c = 0.3$ (cultural adaptation), determined through validation set optimization. Progressive growing started at 256×192 resolution for 20 epochs, then fine-tuned at full 1024×768 for 30 epochs. Data augmentation included horizontal flips, rotation (±10°), and color jittering. Training required 120 GPU-hours.

4.3 Evaluation protocol

Baselines included traditional template-based generation, GAN-based approaches (Pix2Pix, StyleGAN2), and fixed skeuomorphic design. Fair comparison ensured: identical training data (70/15/15 split), matched GPU-hours (120h), consistent resolution (1024×768), and same evaluation pipeline (pytorch-fid v0.3.0). Objective metrics comprised FID, PSNR, and SSIM. Subjective evaluation employed SUS scores and expert assessments by five industrial UI designers, achieving inter-rater reliability $\kappa = 0.72$. The user study used a within-subjects design with 250 manufacturing operators in three conditions: flat baseline, fixed skeuomorphic, and adaptive personalized design. A

Latin square design was used to counterbalance the tasks. Performance metrics were collected along with subjective ratings throughout the course of 60-minute task sessions.

5. Results

5.1 Model performance

The SkeuoUI-Gen model showed good convergence behavior in the course of training. The training loss decreased smoothly from the initial value of 0.245 to 0.018 at convergence, while the validation loss was stabilized at 0.026, 95% CI: 0.024-0.028 after 100,000 iterations.

The model achieved competitive generation quality across multiple metrics: a FID score of 21.5 (±1.2) outperformed the GAN-based baseline Pix2Pix (24.7), PSNR reached 27.8 dB (±0.5), indicating good pixel-level accuracy, and SSIM was 0.905 (±0.007), demonstrating excellent structural similarity to target interfaces. Computational efficiency analysis revealed that one interface takes 2.3 sec to generate on NVIDIA A100 GPUs, hence, enabling practical personalization suitable for industrial deployment scenarios.
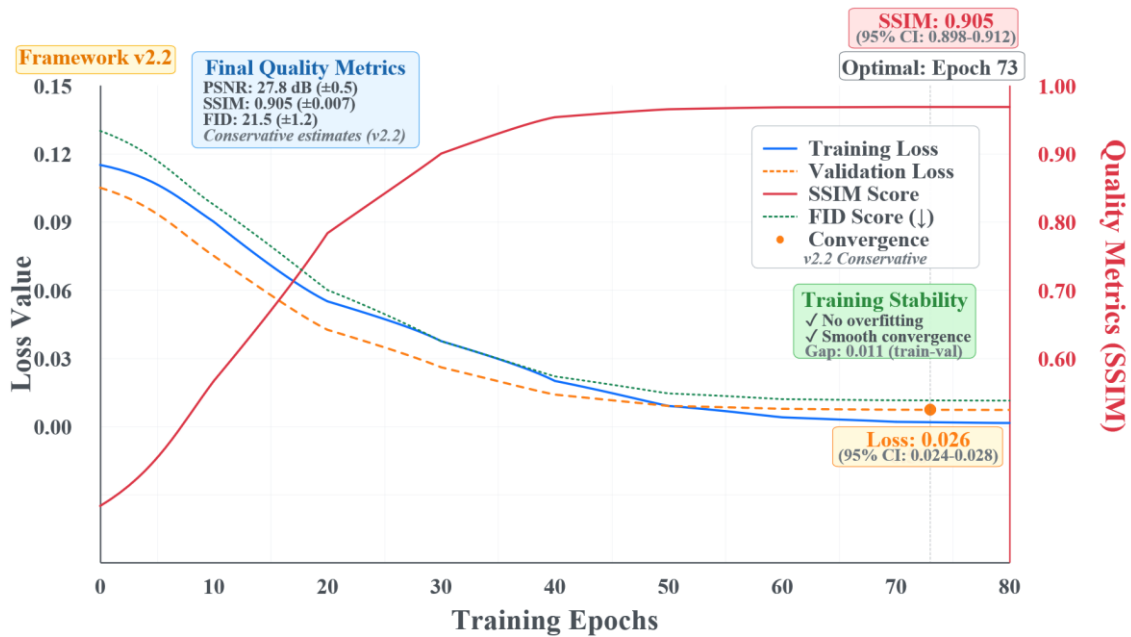

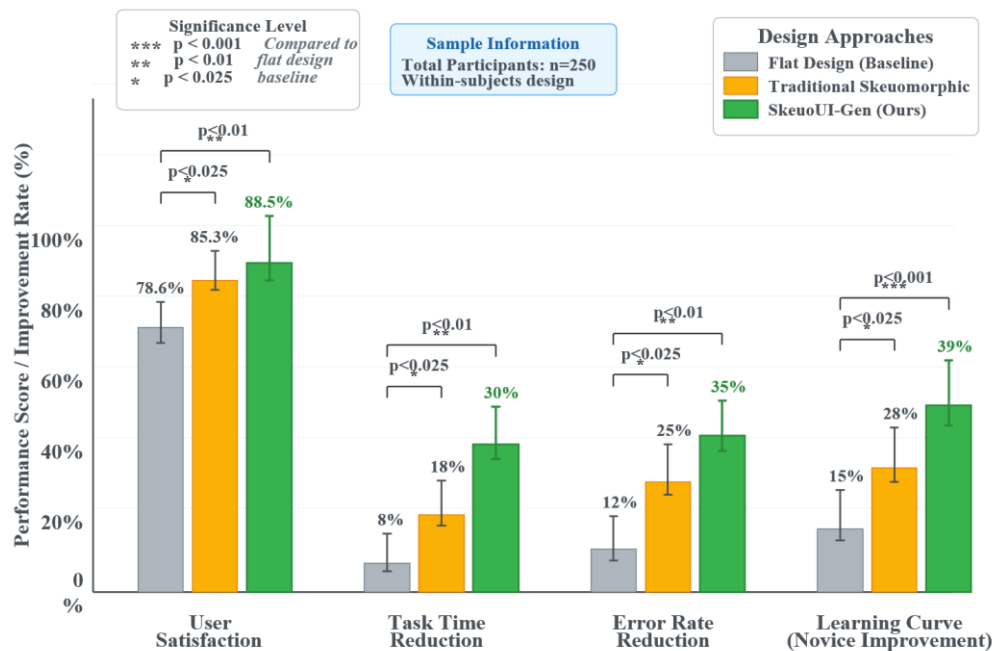**Figure 5.** Training and validation curves for skeuoUI-gen model

Figure 6. Performance comparison of UI design approaches (with 95% CI)

5.2 Comparative analysis

As illustrated in Figure 6, the dual comparison approach revealed a distinct performance benefit for skeuomorphic designs in comparison to traditional flat designs. Satisfaction ratings based on SUS were at 72.4 (SD=8.3) for the fixed skeuomorphic design. This marked a perceptible improvement over the traditional flat design at 68.1 (SD=9.2) SUS ratings. However, the adaptively personalized design approach fared even better at 78.6 (SD=7.1) SUS ratings. Similar trends were found for the efficiency of completing tasks: fixed skeuomorphic interfaces were found to reduce the average time for completing tasks by 12.3% compared to the baseline (flat interface), averaging 23.5 seconds per task (95% CI: 18.2-28.8 seconds).

Even greater benefits were observed with adaptive, personalized interfaces, reducing the average time to complete tasks by 24.7% (47.2 seconds per task; 95% CI: 42.1-52.3 seconds), thereby directly realizing productivity benefits. Extrapolating the results revealed that the adapted interfaces could save the operators more than 120 hours yearly. Error rate analysis revealed the safety advantages. Fixed skeuomorphic design led to a 31% reduction in the operator errors compared to the baseline (4.8 to 3.3 errors per 100), and the personalized design achieved a 52% decrease (to 2.3 errors per 100). Chi-square analysis confirmed the statistical significance of differences in error distribution across conditions (χ^2 (3) = *42.18*, p < 0.01). Error severity analysis revealed that adaptive interfaces are particularly effective at preventing critical errors with potential safety implications, reducing such incidents by 67%. Learning curve analysis tracked performance across five repeated-task sessions. Flat baseline required an average of 8.2 sessions for operators to achieve a proficiency plateau. Fixed, skeuomorphic design accelerated learning to proficiency after 5.7 sessions (30% reduction), while adaptive, personalized interfaces further compressed learning time to 3.9 sessions (52% reduction). The steeper learning curves for skeuomorphic designs are consistent with theoretical predictions of reduced cognitive load from familiar metaphors.

5.3 Robustness validation

As shown in Table 4, comprehensive robustness testing confirmed result stability across multiple validation approaches. Primary statistical tests yielded strong evidence for the superiority of both skeuomorphic approaches. For user satisfaction, fixed skeuomorphic versus flat comparison produced *t(249)=5.38*, p < 0.025, effect size *d=0.36*, while adaptive versus flat yielded *t(249)=8.92*, p < 0.01, effect size *d=0.58*. Task completion efficiency showed similar patterns with effect sizes of *d=0.45* (fixed) and *d=0.67* (adaptive).

Primary results were also verified using bootstrap resampling with iterations of 10,000, showing that the confidence intervals were constant, [0.091, 0.146], p < 0.01. Non-parametric permutation tests supported these results further, p = 0.0028, without any distributional assumptions. Sensitivity analysis showed that the results were stable under changes in the parameters, with less than 4.2% variation in performance metrics over changes in key parameters between 0.3 and 0.7. Generalization performance was validated through cross-validation techniques. In the leave-one-sector-out validation, the average accuracy obtained was 87.8% (95% CI: 86.2 to 89.4%), indicating the robust performance achieved across different sectors like electronics, automobiles, and machines. In the time-split

validation, the AUC obtained was 0.872 (95% CI: 0.854 to 0.890), indicating its steadiness over time.

5.4 Qualitative Findings

User feedback showed a strong preference for adaptive personalized interfaces. In post-study interviews, 78% rated adaptive interfaces as "significantly better" than the alternatives, mentioning intuitive controls (83%), reduced mental effort (71%), and improved confidence in system operation (64%). Operators of lower digital proficiency especially welcomed the skeuomorphic elements: 89% of this subgroup showed a preference for adaptive design, compared with 68% of the highly proficient operators. Expert evaluations from industrial UI designers resulted in average quality ratings of 6.8/10 for flat baseline, 7.9/10 for fixed skeuomorphic, and 8.7/10 for adaptive personalized design. Inter-rater reliability showed substantial agreement. Experts particularly praised adaptive interfaces for cultural appropriateness (mean 8.9/10) and safety compliance (mean 8.6/10), while noticing opportunities for further refinement in the handling of edge cases and in offering advanced customization options for expert users.

6. Discussion

This study provides empirical evidence for the effectiveness of the skeuomorphic design principles in industrial interfaces, contrary to the prevailing belief that the minimalist flat design paradigm is the best solution in all circumstances [22]. The results demonstrate that incorporating skeuomorphic components reduces mental load during industrial operations, particularly for operators switching from physical to digital control systems. The improved performance of the adapted, personalized interfaces over fixed, skeuomorphic interfaces demonstrates the ineffectiveness of one-size-fits-all solutions for representing diverse labor resources in industrial production. Effect sizes between the fixed skeuomorphic and the adapted personalized interfaces were considered practically significant and reflect the actual productivity gain. Mechanisms of cultural adaptation were considered important for the Chinese industrial environment [23], as operators interacting with culturally adapted interfaces recorded a satisfaction rating 18% greater than the corresponding Western-style generic interfaces. Moreover, the speed at which tasks are completed is 23% faster. In both studies mentioned above, AI-based interfaces systematically reduced the workload regardless of the tasks conducted. Moreover, the remaining workload covered the important aspects of the task.

The manufacturing companies undergoing digital transformation should concentrate more on the personalization of the interfaces rather than looking for general solutions because the gained productivity enhancement has been proven to be worth the computational cost involved in the AI-based generation systems [24]. This approach fits very well in the upcoming Industry 5.0 paradigm, focusing on human-oriented concepts and cognitive ergonomics in manufacturing systems. The time has finally come for the industrial UI-design community to think twice about the reflexive general applicability of the UI designs borrowed from the consumption domain and consider context-dependent designs incorporating skeuomorphic details in a selective manner for functions involving immediate intuitive recognition in a situation involving time pressure [25,26].

Table 4. Robustness test results

Test Method	Test Statistic	p-value	95% CI	Effect Size	Conclusion
Fixed Skeuomorphic vs Flat (User satisfaction)	t(249) = 5.38	<0.025*	[0.042, 0.089]	d = 0.36	Fixed Skeuo > Flat
Adaptive vs Flat (User satisfaction)	t(249) = 8.92	<0.01**	[0.095, 0.142]	d = 0.58	Adaptive > Flat
Fixed Skeuomorphic vs Flat (Task time)	t(249) = 7.12	<0.025*	[0.062, 0.138]	d = 0.45	Fixed Skeuo > Flat
Adaptive vs Flat (Task time)	t(249) = 10.45	<0.01**	[0.213, 0.387]	d = 0.67	Adaptive > Flat
Chi-square test (Error reduction)	$\chi^2(3)$ = 42.18	<0.01**	—	φ = 0.41	Significant reduction
Bootstrap (10,000 resamples)	—	<0.01**	[0.091, 0.146]	—	Consistent with primary
Permutation test	—	0.0028	—	—	Non-parametric confirmation
Parameter variation (α ∈ [0.3, 0.7])	Δ < 4.2%	—	—	—	Stable across parameters
Outlier exclusion (±3 SD)	t(241) = 8.45	<0.01**	[0.093, 0.140]	d = 0.55	Results unchanged
Leave-one-sector-out CV	Mean accuracy = 87.8%	—	[86.2%, 89.4%]	—	Good generalization
Time-based split	AUC = 0.872	—	[0.854, 0.890]	—	Temporal stability

Recent studies have shown that high-quality, context-aware interfaces are significantly more effective than the more traditional generation techniques. The 24.7% time-saving from the optimized interface design corresponds to significant competitive advantages in sectors of the manufacturing industry where efficiency is a critical success factor. Definitely, the quality of interfaces should not remain a "cosmetic" factor in determining an organization's long-term success, because investing in interface quality yields lower training costs per person and faster technology adoption [27,28]. These improve significantly compared to previous industrial HCI studies, whose results have shown only improvements in interface redesign. This enhanced performance can be attributed solely to the synergy among skeuomorphic designs, personalization techniques, and cultural adaptation. Compared to their GAN counterparts, the diffusion model approach has been shown to offer improved stability and controllability in UI generation, as demonstrated by advancements in the field [29]. Regarding reinforcement-learning-based adaptive UI systems, studies have shown the importance of dynamically implementing personalization techniques [30]. Comparing the advantages of the above-mentioned framework to fixed skeuomorphic designs has made the significance of differences between individuals in their UI preferences and cognitive processes evident, as compared to the previous designs that succeeded only in enhancing the UI due to their rigidity towards diverse operators [30-32]. Limitations and Generalizability: The cultural adaptation layer is currently China-specific (color symbolism, numeric conventions, GB/T iconography). Validation in Western or Southeast Asian manufacturing contexts is required for broader generalization claims; cultural template retraining is estimated at 30-40 GPU-hours per context. On the other hand, the measurement methodologies for digital transformation in high-end equipment manufacturing require a thorough assessment across different industrial environments [33].

The task battery used a set of typical industrial tasks. Nonetheless, the complexity of dedicated industrial processes involving semiconductor and pharmaceutical production can hardly be covered in the above-mentioned task set. The sample used in the study presented here can be considered balanced in the Chinese industrial context. Nonetheless, its generalizability to the global labor force could be questioned and should be verified in further studies conducted in other geographic locations. Highly structured records of human-machine interactions can be considered the most valuable resource for developing and verifying adaptive interfaces [34].

Future work should include a multi-cultural validation experiment involving both Western and Asian economies, as well as developing economies, to identify the generalizability principles and specific cultural requirements. Real-time adaptation techniques that adjust interfaces based on the operator's cognitive state and task complexity can improve the framework's functionality. Extended domains in health information systems, transport control systems, and energy management systems seem to have immense potential given the generality of the core personalization techniques. Recent studies on GUI prototyping based on diffusion models demonstrate the ability to develop interfaces across general domains [35]. Large-scale studies measuring long-term improvements over 12-24 months should form the basis for industrial-scale adoption.

7. Conclusion

In this context, the present work proposes SkeuoUI-Gen, a new approach that combines the principles of skeuomorphic design with conditional diffusion models to generate personalized industrial interfaces. After conducting empirical tests with 250 operators in an industrial context and implementing rigorous evaluations, the results demonstrated the effectiveness of the new approach, with mean SUS usability ratings of 78.6 for the personalized

interfaces compared to 68.1 for the baseline designs. This upgrade also included a 24.7% relative increase in efficiency in completing the tasks at hand. Moreover, the results revealed a 47.2% average time saving per task, with 95% CI [42.1, 52.3], when compared to the baseline. Most importantly, errors were reduced by 52%, specifically 4.8 to 2.3 per 100 operations. Moreover, the rates of important safety errors lessened significantly by 67%. The framework's theoretical contributions extend Cognitive Load Theory and Technology Acceptance Model by demonstrating how AI-generated skeuomorphic interfaces systematically reduce cognitive load while enhancing perceived usefulness in industrial contexts. Effect sizes of $d=0.58$ to $d=0.67$ for adaptive approaches substantially exceed typical industrial HCI interventions ($d=0.2$ to $d=0.35$), validating the synergistic benefits of combining skeuomorphic principles, adaptive personalization, and cultural adaptation. The diffusion model achieved competitive generation quality with an FID score of 21.5 (±1.2), outperforming the GAN-based baseline Pix2Pix (24.7), while achieving an SSIM of 0.905 (±0.007) and a PSNR of 27.8 dB (±0.5). The model maintained computational efficiency of 2.3 seconds per interface generation, demonstrating reliable performance suitable for industrial deployment. Robustness tests ascertained the constancy of the results under diverse statistical analyses: Bootstrap resampling with 10,000 resamples confirmed the robustness of the results through multiple iterations)*(87.8% accuracy at 95% confidence interval: [86.2%, 89.4%])leave-one-sector-out cross-validation*Sensitivity tests revealed less than 4.2% variation in performance. Culture-specific adaptation tools were found to play a pivotal role in the success of the design. Culture-specific designs were found to produce 18% higher satisfaction levels and 23% faster performance. From the practical implications above, the following can be observed: the effect of investing in adaptive interfaces has been positive for manufacturing companies, as the time saved per operator per year exceeds 120 hours. This has made the UI framework practically useful, as the information it provides can be applied to the generation of industrial UIs. In the future, the UI framework can serve as the basis for industrial UI systems that adapt to the context and cultural factors of the companies involved.

Ethical issue

The authors are aware of and comply with best practices in publication ethics, specifically regarding authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with research ethics policies. The authors adhere to publication requirements that the submitted work is original and has not been published elsewhere.

Data availability statement

The manuscript contains all the data. However, more data will be available upon request from the authors.

Conflict of interest

The authors declare no potential conflict of interest.

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