ChatGPT

# Literature Review: Evaluating Digital Avatar Performance and User Acceptance Across Diverse Demographic Groups

## Introduction

This literature review surveys recent peer-reviewed research (2010–2025) relevant to *"Evaluating Digital Avatar Performance and User Acceptance Across Diverse Demographic Groups: A Cross-Cultural Assessment."* Six key areas are examined: **(1)** algorithmic bias in AI-generated content, **(2)** digital avatar and virtual human research (realism, uncanny valley, embodiment, cross-cultural perception), **(3)** cultural representation in digital media, **(4)** voice synthesis and speech technology bias, **(5)** user experience and technology acceptance, and **(6)** ethics and social implications (including deepfakes, identity, and biometric privacy). Within each area, we highlight major findings, methodologies (e.g. bias detection metrics, evaluation frameworks), demographic factors, and author-noted limitations. Citations are formatted in AMA style.

## Algorithmic Bias in AI-Generated Content

**Prevalence and Impact of Bias:** A substantial body of work shows that AI systems can exhibit systematic racial, gender, and ethnic biases, reflecting inequalities in training data and design [1]. For example, Buolamwini and Gebru's landmark study of commercial facial-analysis algorithms revealed striking accuracy disparities: error rates for classifying gender were as low as 0.8% for light-skinned males but soared past 20–34% for darker-skinned females [2]. Such bias not only undermines performance for marginalized groups but can perpetuate harmful stereotypes in automated decisions [3]. The implications span domains like hiring, policing, healthcare, and content generation. A recent survey emphasizes that generative AI *itself* can reproduce and amplify societal stereotypes in the media it creates [3]. For instance, Stable Diffusion (a popular text-to-image model) was found to output racially biased imagery when generating people: across prompts involving professions and attributes, the model over-produced certain demographics and portrayed culturally stereotypical features (e.g. nearly all "Middle Eastern men" were depicted with beards, traditional clothing, and similar appearance). These biases in generative content can reinforce viewers' prejudices; indeed, an experiment showed that exposing people to *non-inclusive* AI-generated face sets actually increased their implicit racial/gender biases, whereas *inclusive* and diverse outputs reduced biases. Taken together, the literature underscores that algorithmic bias in AI-generated human-like content is a real and measurable problem with social consequences, necessitating robust detection and mitigation strategies [4].

**Detection and Quantification Methods:** Researchers have developed various methodologies to detect and quantify bias in AI models, often adapting fairness metrics from machine learning. Common **fairness metrics** include statistical parity, equal opportunity, and disparate impact, which measure how outcome probabilities differ across groups [5]. For example, one systematic review noted that multiple studies detected "implicit and algorithmic biases" by computing metrics like statistical parity (difference in positive outcome rates between groups) and equal opportunity (difference in true positive rates) [6]. Benchmark audits are also used: Buolamwini & Gebru's approach of disaggregating model accuracy by intersectional demographic groups (race × gender) is a template for auditing AI systems [2]. In content generation, bias can be quantified by analyzing model outputs for representation discrepancies or stereotypical portrayals, as seen in the Stable Diffusion audit above. Another methodology is user studies; for instance, researchers conducted surveys where participants rated AI outputs, revealing how biased imagery can shape human attitudes.

**Bias Mitigation Strategies:** To address bias, the literature documents interventions at multiple stages of the AI pipeline. Pre-processing steps include curating more diverse training datasets and rebalancing data (through oversampling or reweighting under-represented groups) [7]. In-processing techniques involve algorithmic adjustments like fairness constraints or modified loss functions to penalize biased outcomes. For example, generative model researchers have proposed allowing users to *constrain* output demographics (e.g. explicitly specify a desired distribution of genders/races in generated avatars) to counteract a model's inherent biases. Post-processing can also help, such as filtering or adjusting outputs that exhibit unwanted bias. A review of bias in AI for healthcare noted that most mitigation efforts so far rely on data-level solutions (e.g. resampling) and call for more standardized reporting of bias evaluation in studies [8]. Despite these efforts, authors frequently acknowledge limitations: bias mitigation often involves trade-offs with model accuracy, and what "fairness" means can vary by context [9]. Moreover, many bias audits focus on specific attributes (like race or gender) and may not capture more subtle or intersectional biases. The evolving consensus is that no single metric or fix suffices; a combination of **transparency, diverse inclusive data, ongoing audits, and multidisciplinary oversight** is needed to ensure AI-generated content is fair and trustworthy [10].

*Key methodologies for bias detection and mitigation in human-like AI content include:*

- **Fairness Metrics & Benchmarks:** Quantitative measures (e.g. statistical parity, equal opportunity) to detect outcome disparities [5]. Demographic-specific evaluation benchmarks (like "Gender Shades") reveal performance gaps by race/gender [2].
- **Data Audits & Curation:** Examination of training data for representation gaps (e.g. over 40% of avatars in a popular 3D library were white males [11]). Enriching data with minority groups or synthetic augmentation to balance inputs [12].
- **Algorithmic Debiasing:** Incorporating fairness constraints or reweighting during model training [13]. E.g., adjusting an image generation model to produce a demographically specified mix of outputs to avoid homogenization.
- **Post-processing Filters:** Removing or modifying biased outputs after generation (for instance, detecting and altering stereotyped depictions). Also, providing transparency via model cards or bias impact statements (to inform users of known biases).

## Digital Avatars and Virtual Humans: Realism, Uncanny Valley, and User Acceptance

Research on digital avatars – computer-generated virtual humans – has grown, examining factors that drive user acceptance, perceived realism, and the eerie *"uncanny valley"* effect. A core question is how human-like an avatar should be to maximize engagement without provoking discomfort. Early theories posited that as a synthetic character's realism increases, people's affinity grows – until a point where *almost* human-looking avatars elicit unease (the uncanny valley). Recent studies put this theory to empirical test across cultures and use-cases.

**Realism vs. Uncanny Valley:** Sharma and Vemuri (2022) conducted a series of experiments to probe acceptance of highly realistic avatars in social and professional roles [14]. In one experiment, participants watched clips from a film in both CGI-animated and live-action forms to compare perceptions. In another, they viewed *hyper-realistic* digital avatar clips and reported on recognition (distinguishing avatar from real), eeriness, and which facial features seemed "off." Using eye-tracking, the researchers measured visual attention (gaze fixations on avatar faces vs bodies) and pupil dilation as an index of emotional arousal (e.g. fear or eeriness) [15]. Interestingly, the uncanny valley effect was not as straightforward as theory predicts: the **eerie ratings did not strictly increase** at highest realism. In fact, with today's high-quality CGI and motion-capture, the avatars may have "crossed the valley," achieving realism that evoked similar gaze patterns and attention as real humans [16]. Participants' pupils did dilate during certain avatar movements (like talking or smiling), indicating some residual eeriness or subconscious response [17]. Crucially, when asked about accepting avatars in various roles, people were *less* willing to embrace digital humans in roles requiring complex social skills (e.g. as a friend or a judge), compared to simpler roles [18]. This suggests that even if visual realism is high, **trust and acceptance lag for avatars in high-empathy, high-stakes roles**. Another notable finding was that **real-world stereotypes transfer to virtual agents**: participants rated avatar performance in gendered roles in line with gender biases (e.g. female-presented avatars judged less favorably in traditionally male roles and vice-versa) [18]. The authors conclude that acceptance of human-like avatars is *ambiguous* and context-dependent – simply improving visual fidelity may not guarantee trust for all purposes [19]. They argue for a multidimensional approach beyond uncanny valley theory, considering social and cognitive factors in avatar design and deployment [19].

**Embodiment and Presence:** In interactive settings like virtual reality (VR), a key aspect of avatar performance is *embodiment* – the extent to which users feel that a virtual body is their own. A 2024 study by Do et al. investigated how matching an avatar's demographics to the user's affects the user's *sense of embodiment (SoE)*, and notably, how this might differ across participant groups [20]. In a controlled VR experiment with 78 diverse participants, each person embodied avatars that either **matched** or **mismatched** their own ethnicity and gender [21]. The results revealed significant demographic effects: *participant ethnicity* emerged as a factor in embodiment. Asian and Black participants reported **lower overall embodiment** scores (on standardized questionnaires) compared to Hispanic participants, regardless of avatar matching [22]. Moreover, when looking at the "ownership" subscale of SoE (feeling the avatar's body as one's own), Asian and Black users showed a **stronger benefit from ethnically-matched avatars** than White users did [23]. (Hispanic participants showed no significant difference between matched vs. mismatched, suggesting a more complex identity dynamic [24].) These nuanced findings highlight that avatar acceptance is not one-size-fits-all – cultural or racial identity can influence how readily a user identifies with a virtual body. Designing avatars that users can identify with may thus require culturally mindful customization. The authors note one limitation that their sample, while balanced, was U.S.-based; cross-cultural studies (with participants *in* different countries) would further illuminate how cultural background and exposure affect embodiment [20].

**Cross-Cultural Perception:** Cross-cultural differences also appear in how people perceive and respond to human-like agents broadly. Castelo et al. (2022) compared American and Japanese participants' comfort with humanoid robots to test the universality of the uncanny valley. They found stark differences: as a robot's human-likeness increased (both in appearance and behavior), *American* participants' comfort levels **decreased** significantly – consistent with uncanny valley expectations – but *Japanese* participants did **not** experience this drop in comfort. Japanese users were generally more accepting of highly humanlike robots, possibly due to cultural factors (e.g. Japan's familiarity with social robots and animist attitudes seeing robots as having "spirit"). This suggests culture moderates the uncanny valley; familiarity and cultural narratives around humanoid figures can soften or eliminate the eerie feeling. Although this study was with physical robots, the implication for digital avatars is parallel: **cultural context shapes avatar acceptance**. Indeed, researchers stress designing avatars with *cultural appropriateness* – matching cultural norms, appearance, and communication style – to improve user experience across different user groups. For example, an avatar interface study found that users respond more positively when avatar aesthetics and behaviors align with their cultural expectations and values [12] [25]. Avatars that unintentionally violate cultural norms (even subtle cues like eye contact, gestures, or attire) risk alienating users from that culture. However, detailed cross-cultural avatar studies remain relatively few; many experiments use WEIRD (Western Educated) participant samples, which authors cite as a limitation. Going forward, broader participant recruitment and collaboration with international researchers are recommended to ensure findings generalize globally.

## Evaluation Metrics for Avatar Realism and User Acceptance

Researchers employ a variety of **validated metrics and frameworks** to evaluate how "real" an avatar appears and how readily users accept or trust it:

- **Uncanny Valley Questionnaires:** Subjective rating scales capture users' eeriness or discomfort toward near-human avatars. Participants typically rate how *eerie*, *uncomfortable*, or *strange* an avatar appears. Divergence in eeriness scores as human-likeness increases can indicate an uncanny valley effect [26]. Some studies also ask for *realism* ratings or whether the avatar is believed to be real or artificial [27].
- **Sense of Embodiment (SoE) Scales:** In VR and AR contexts, standardized questionnaires measure embodiment, often with subcomponents: **ownership** (feeling the avatar's body as one's own), **agency** (feeling in control of the avatar's actions), and **presence** (sense of "being there" in the virtual world). Higher SoE indicates better avatar integration with the self. Do et al. used SoE to quantify the impact of avatar-user demographic matching [22]. SoE scales have been validated in prior VR research and are crucial for assessing user comfort in avatar embodiment scenarios.
- **Behavioral and Physiological Metrics:** Eye-tracking provides objective insight into user responses. Metrics like **gaze fixation** (where people look) can show if users avoid looking at an uncanny face, and **pupil dilation** can indicate emotional arousal (e.g. fear or surprise) when viewing an avatar [15] [17]. These measures complement self-reports by uncovering subconscious reactions. Other behavioral measures include response time in recognizing an avatar as artificial or memory tests (did the user recall the avatar's appearance correctly), which gauge how convincingly realistic the avatar was.
- **Technology Acceptance Surveys:** To evaluate user acceptance more broadly, researchers often adapt models like the **Technology Acceptance Model (TAM)** or Unified Theory of Acceptance and Use of Technology (UTAUT). These frameworks involve constructs such as **Perceived Usefulness**, **Perceived Ease of Use**, **Trust**, and **Intention to Use**. For instance, in evaluating virtual health agents for older adults, Wang et al. found that *perceived usefulness* was a strong direct predictor of intent to use, and *ease of use* influenced intention indirectly via increasing trust and usefulness [28]. Such surveys, when tailored to avatars or AI systems, quantify user attitudes and acceptance levels. A related metric is **credibility/trust scales** – users rate how much they trust the avatar or find it credible as an information source or social actor. High trust correlates with higher acceptance in roles like virtual assistants or teachers.

Researchers often use a **mixed-methods** approach, combining the above measures. For example, Sharma & Vemuri's work combined subjective eeriness ratings with eye-tracking data and acceptance surveys for different roles [29] [18]. This triangulation strengthens validity. Limitations in measurement are acknowledged: subjective scales can be influenced by individual interpretation or cultural factors, and physiological measures require careful lab setup. Still, these metrics and frameworks have become standard toolkits to rigorously evaluate avatar performance and user acceptance.

## Cultural Representation in Digital Media

A recurring theme in the literature is the importance of accurate and inclusive cultural and ethnic representation in digital media, including avatars, games, and AI-generated characters. Poor representation can manifest as stereotypes, biases, or exclusion of certain groups, which in turn affect user acceptance and perpetuate social biases.

**Stereotypes and Representation Gaps:** AI-generated media and virtual characters have at times reproduced troubling cultural stereotypes. The earlier example of Stable Diffusion homogenizing Middle Eastern men with a single stereotypical look illustrates how generative models can *bake in* cultural caricatures. Such outputs reflect biases in training data (e.g. images scraped from the web that over-represent certain stereotypical depictions). Similarly, Sharma & Vemuri observed that participants carried real-world gender stereotypes into how they judged avatars' abilities, indicating digital avatars can inherit the bias of their users or creators [18]. In gaming and virtual worlds, researchers have noted that **avatar customization options** often default to Eurocentric features and lighter skin tones, implicitly marginalizing users of other ethnicities. Until recently, many off-the-shelf avatar libraries had limited racial diversity – for example, one widely used "Rocketbox" avatar set was reported to have over 40% of characters as white male, and only token options for other races [11]. Profession attire for minority avatars was also lacking (e.g. no Asian doctor avatars in that library) [30]. The **lack of diverse avatar assets** not only diminishes representation for users but also *skews research*: as one paper noted, studies on diversity effects were constrained by the available avatars, potentially introducing bias "from the outset" of experimentation [12]. This recognition has led to projects like the VALID avatar library (Virtual Avatar Library for Inclusion and Diversity) which explicitly provides a balanced set of avatar models across races, genders, and professions [25]. By validating these avatars through user perception studies, the goal is to enable more culturally inclusive research and applications.

**Cross-Cultural Design and Appropriateness:** Beyond visual representation, cultural factors include language, communication style, and norms embedded in virtual humans. Avatars intended for cross-cultural audiences must be designed with cultural **appropriateness** to avoid offense and improve engagement. For instance, an interface avatar for users from an Arabian culture was found to be more effective when it followed cultural expectations in clothing and etiquette, compared to a generic Western-style avatar (study reported in abstract, source accessible via ScienceDirect). In human-computer interaction (HCI) research, *cross-cultural design* has grown as a field addressing how user interface elements (like avatars) can be tailored to different cultural contexts [31]. One key finding is that *culturally congruent avatars* can enhance user comfort and trust. This might involve offering avatars with ethnically appropriate facial features, skin tones, or voices that resonate with the user's background, as well as culturally relevant behaviors (gestures, formality level, etc.). Conversely, misuse of cultural symbols or misrepresentation can lead to user disengagement or even backlash. Researchers emphasize participatory design with target cultural groups to ensure authenticity and respect. However, authors also note practical limitations: it's impossible to represent every cultural nuance, and individuals within a culture are diverse. What matters is providing *options* and avoiding one-size-fits-all defaults that inadvertently center one culture as the norm [11] [25]. Increasing the **diversity of content creators and datasets** is seen as part of the solution – if more voices from different cultures are involved in avatar development and training data curation, the resulting media are less likely to reinforce stereotypes.

**Impact on Users:** Why does representation matter? Studies show that representation can affect users' identity, performance, and even biases. For example, a phenomenon called the **Proteus effect** in virtual environments suggests that the attributes of one's avatar can influence one's behavior and self-perception. When users from minority groups finally see relatable avatars, it can boost their engagement and sense of belonging. On the flip side, being limited to non-representative avatars (or seeing one's group portrayed stereotypically) can diminish involvement. One experimental study found that when racial minority participants used avatars with a *visible diverse representation* in a virtual world, they expressed themselves more freely and felt more included compared to when all avatars were homogeneous [32] [33]. Furthermore, immersive VR studies where participants embody avatars of a different race have revealed fascinating effects on prejudice: embodying a darker-skinned avatar, for instance, has been shown to *reduce implicit racial bias* in white participants in several experiments [34]. This line of work (Peck et al. 2013; Groom et al. 2009, etc.) leverages representation to foster empathy – literally putting someone "in another's shoes." It underlines the power of avatars not just to reflect social reality, but to potentially *reshape* it in positive ways if used conscientiously. Researchers caution, however, that these effects can be context-dependent and temporary; long-term attitude change likely requires broader educational interventions.

In summary, ensuring **cultural representation and avoiding stereotypes** in digital avatars is both an ethical imperative and a factor in user acceptance. The literature suggests moving beyond token inclusion toward genuine cultural **co-design**, richer avatar customization options (so users can create avatars that truly represent them), and continual audits of AI content for biased representations. Many papers echo the sentiment that inclusive design is an ongoing process – as one study put it, technological advancements have "placed humans closer to co-existing with digital or physical humanoids," making it *crucial* that those digital humans reflect the rich diversity of their human counterparts [35].

## Voice Synthesis and Speech Technology Bias

Human-like AI extends beyond visuals to **voice and speech**, where biases can also emerge. Modern text-to-speech (TTS) systems and voice recognition assistants have made great strides in realism, but research reveals performance disparities across accents, dialects, gender, and age groups. These biases in voice AI can lead to unequal user experiences – for instance, some users consistently find that "the AI doesn't understand my accent" or that a synthesized voice "doesn't sound like me."

**Accent and Dialect Bias:** A notable study by Koenecke et al. (2020) examined leading automated speech recognition (ASR) services from big tech companies for racial disparities [36]. They found that the systems had **significantly higher error rates for Black speakers** compared to white speakers. On average, the word error rate was 35% for Black voices versus 19% for white voices – nearly double the errors [36]. This gap persisted even when Black and white individuals spoke the exact same phrases, implicating the acoustic models and data as the source of bias [36]. Such findings confirm that voice technologies trained predominantly on standard American English end up less accurate for speakers with African American Vernacular English (AAVE) features or other dialects. Similarly, other research on accent bias finds that ASR performs worse on regional accents and non-native English speakers [37] [38]. The practical consequences range from inconvenience (voice assistants mishearing commands) to safety risks (if, say, an emergency hotline AI fails to understand a caller's accent). One recent 2025 study evaluated AI text-to-speech services (for audiobook narration and voice cloning) across five English accents (e.g. British, Indian, Australian, etc.)

[39]. It found **technical performance disparities**: certain accents yielded more errors or unnatural prosody in the synthesized speech [40]. Moreover, through user interviews, the authors discovered that people with distinct accents felt the synthesized voices "did not represent them" and that current voice AI might reinforce a bias toward privileged accents (e.g. treating a mid-Atlantic American accent as the default of "clear" speech) [41]. These outcomes underline the concept of *linguistic privilege*: voice AIs tend to cater to majority or prestige accents, thereby marginalizing others. The recommendation is clear – developers must train and evaluate speech models on diverse linguistic data and possibly allow user tuning for accent to make voice tech more inclusive [40].

**Gender and Age Bias in Voice Systems:** Bias issues also intersect with gender and age. Historically, many voice assistants defaulted to a **female-sounding voice**, which has been critiqued for reinforcing gender stereotypes (the subservient "female secretary" trope). While some platforms now offer multiple voice options, studies of user preference indicate a complex mix of social conditioning in why female voices were preferred for assistive roles. On the performance side, ASR systems have shown slightly higher error rates for female speakers than male in some cases – possibly because of lower representation of female voices in training or pitch differences. Likewise, **children's speech and elderly speech** often see higher ASR error rates since these age groups have acoustic characteristics underrepresented in training data (children have higher pitch and different enunciation; older adults may have weaker vocal output or accents shaped by region and era). A 2023 systematic analysis quantified ASR bias across gender, age, and accent, confirming statistically worse performance on female voices, on voices over age 60, and on non-standard accents [42]. These biases can lead to practical exclusion – e.g., older adults being less able to use voice-activated devices reliably. Researchers are addressing this by creating specialized datasets (like children's speech corpora, regional accent datasets) and adapting models through transfer learning to these groups. Another angle is user personalization: some speech systems now calibrate or "learn" a user's voice over time. However, author-identified limitations include the risk of *overfitting* to frequent users while not generalizing well to new users with different speech profiles.

**Voice Synthesis and Representation:** In generative voice AI (cloning a person's voice or generating voices from text), fairness involves whose voices are used and how. There is concern about accent portrayal: if an AI voice generator is asked to produce, say, an Irish or Nigerian accent, does it do so accurately or does it fall into caricature? Bias can also mean *which voices are available*: are most TTS voices middle-aged, adult voices? Few systems offer child-sounding voices or very elderly-sounding voices, which might be important for applications like games or assistive tech for those demographics. The 2025 study by Michel et al. found that current voice cloning tech may inadvertently propagate *accent-based discrimination* – for example, one service might output a "neutralized" accent even when cloning a person with a distinct regional accent, effectively erasing part of that person's vocal identity [41]. Participants in that study voiced that "it's not a representation of me" when their accent did not come through in the AI-generated voice [43]. This raises an ethical design point: should voice AI strive to retain user accents (for authenticity), or is there a bias toward homogenizing speech? As of now, many systems lack explicit controls for this, but awareness is growing.

In summary, **voice AI technologies show measurable biases** related to accent, dialect, gender, and age. These biases mirror the data they learn from and the assumptions of developers. The literature calls for more inclusive training, better evaluation across demographic categories, and user-centered design to accommodate diverse speech. Encouragingly, conferences like *INTERSPEECH* and *FAccT* now frequently feature works on accent fairness and inclusive speech tech. Going forward, the integration of fairness in the design of voice user interfaces (VUIs) will be critical to ensure equitable access – especially as voice-based interaction becomes ubiquitous in smartphones, cars, and IoT devices. As one article title aptly put it, we must move “towards inclusive speech recognition” by systematically quantifying biases and mitigating them [42], to prevent AI from literally silencing certain voices.

## User Experience and Technology Acceptance of AI Systems

The acceptance of digital avatar technology – and AI systems at large – depends not just on the systems’ capabilities, but also on user experience (UX) factors and psychological determinants of technology adoption. Researchers often frame these questions through models like the **Technology Acceptance Model (TAM)** and its successors, examining how factors such as perceived usefulness, ease of use, trust, and social influence affect a diverse range of users’ willingness to adopt AI-driven tools. Here we review findings on user acceptance, with emphasis on demographic variations, trust, and credibility.

**Technology Acceptance Model (TAM) and Trust:** Multiple studies apply TAM or extended TAM models to AI and virtual agent contexts. Consistently, **perceived usefulness (PU)** – the degree to which a user believes a technology will enhance their performance or life – emerges as a strong predictor of intention to use, across demographics [28]. **Perceived ease of use (PEOU)** is also important, often indirectly: if a system is easy to use, users are more likely to trust it and find it useful, thereby increasing adoption [28]. For example, in a study of older adults using virtual health assistant avatars, PU had a direct positive effect on usage intention, while PEOU influenced intention via increasing the user’s *trust* in the avatar [28]. Trust is repeatedly highlighted as crucial for AI systems that act autonomously or provide recommendations. If users do not trust an AI (whether due to lack of transparency, perceived bias, or uncanny behavior), they will reject it regardless of its objective performance. Researchers have incorporated trust into TAM by treating it as either an antecedent or mediator of acceptance. In the above health agent study, *medical presence* (how convincingly the agent mimicked a real doctor’s empathy/presence) boosted trust, which in turn drove intention to use [44]. Transparency and explainability are also factors: users report higher trust when an AI explains its reasoning or shows some accountability for errors.

**Demographic Differences in Adoption:** Studies have revealed that **age, gender, and cultural background** can lead to different attitudes toward AI. A 2024 survey of 2,384 people in Spain investigated how gender and age relate to acceptance of AI and robotics [45]. The data showed women and older adults were significantly **less enthusiastic** about adopting AI/robotics compared to men and younger individuals [46]. Women and seniors expressed more concern about potential negative impacts (e.g. AI causing dehumanization of society), whereas young men had the highest tech optimism [47]. Interestingly, the study did *not* find strong evidence that these groups felt technology would exacerbate inequality (fears of elitism were not strongly supported), but they did worry about loss of human elements in AI-driven future [48]. These findings align with earlier work (Venkatesh & Morris 2000) that found gender and age can moderate TAM factors – for instance, older users may be more sensitive to ease of use, and women’s acceptance might be more influenced by social norms and risk perceptions. Culturally, as discussed in previous sections, familiarity with technology can vary (e.g. Japanese respondents in one study were more accepting of human-like robots than Americans). Emerging economies might have different adoption drivers altogether (such as perceived modernity or economic benefit). One cross-cultural TAM study in Ecuador vs. Russia (referenced in search results) suggested that national context (like economic development and cultural values) influenced which TAM factors were strongest [49]. The upshot is that **user acceptance models should not assume uniform effects across demographics**. Practitioners are urged to consider targeted strategies – for example, to improve older adults’ adoption, interface designers might focus on building trust and providing clearer usefulness benefits, as these can overcome initial reluctance [28]. For female users, addressing ethical and social concerns (showing how an AI is equitable and won’t replace human warmth) may improve acceptance. Meanwhile, tech evangelism among skeptical groups should involve education to demystify AI and mitigate fears.

**User Experience (UX) Factors:** Beyond TAM constructs, general UX principles apply. A positive user experience – intuitive design, pleasant aesthetics, responsive interaction – can make or break acceptance. Avatars with more human-like nonverbal cues (smiling, appropriate eye contact) tend to engender more user satisfaction *if* those cues are done well. But poorly executed cues (awkward smile timing, lifeless voice intonation) create discomfort. This is where UX blends with the uncanny valley: fine details in design affect whether an avatar is seen as creepy or likable. Additionally, **personalization** enhances UX; users are more likely to accept an avatar or AI that they can personalize to their needs or that learns their preferences. However, personalization must be balanced with privacy (users may distrust an AI that collects a lot of personal data to adapt itself). Studies on virtual assistants show that giving users some control – e.g. choosing the avatar's appearance or the AI's voice – increases their sense of ownership and satisfaction, thereby acceptance.

**Credibility and Social Influence:** For AI that provides information or advice (like a virtual agent in education or health), perceived credibility is essential. If users doubt the avatar's expertise or honesty, they will not follow its suggestions. Some papers measured *source credibility* of avatars and found it correlated with more positive outcomes (e.g. an authoritative-looking avatar doctor might instill greater adherence to advice). Social influence also plays a role: if people see peers or society embracing an AI technology, they are more likely to do so (this is encapsulated in the **Subjective Norms** construct in extended TAM/UTAUT). For instance, older adults might be swayed by doctors or family encouraging the use of a health avatar, reducing their mistrust. On the other hand, negative media stories about AI failures can dampen acceptance broadly, a phenomenon noted by authors as an external variable that TAM does not fully capture.

In conclusion, user acceptance of digital avatars and AI systems is multi-factorial. The literature validates classic acceptance models (usefulness, ease, trust) while also pointing to demographic and cultural moderators. Key recommendations include: building **trustworthiness** into AI (through transparency and reliability), involving end-users in design (to ensure the AI meets real needs and is culturally attuned), and addressing specific barriers faced by different groups. As AI proliferates, understanding and improving UX for *all* users – not just early adopters – is critical, or we risk certain populations being left behind by or alienated from new technologies.

## Ethics and Social Implications (Deepfakes, Identity, and Privacy)

The deployment of hyper-realistic digital avatars and AI-generated human likenesses raises profound ethical questions and social implications. Researchers and ethicists are actively exploring issues such as the misuse of deepfakes, identity and representation rights, and the handling of biometric data. The cross-cultural dimension adds further nuance, as perceptions of what is ethical can vary globally.

**Deepfakes and Misinformation:** *Deepfakes* – highly realistic AI-generated fake videos or audio, often swapping identities or altering speech – have garnered intense scrutiny. A 2025 multidisciplinary analysis encapsulated expert consensus that deepfakes pose **significant threats to privacy, public trust, and information integrity** [50]. Malicious deepfakes can be used to spread disinformation (e.g. a fake video of a politician saying incendiary things), to commit fraud (impersonating someone's voice for financial scams), or to harass individuals (as in non-consensual explicit deepfake videos). Experts worry that as this technology improves, it could "erode public trust" in media evidence and inflict psychological harm on victims whose likeness is misused [50]. One key theme is the **democratization of deepfake tools** – they are becoming easier to use, which accelerates both creative uses and abuses. The literature strongly calls for *robust regulatory frameworks* to address deepfakes [51]. Proposals include mandating watermarks or provenance tracking for AI-generated media, and strengthening laws against image-based abuse. Another focus is on societal resilience: improving media literacy so the public can critically evaluate what they see/hear, and not be easily duped by fake content [52]. Interestingly, there is recognition that the *impact of deepfakes can vary by demographic groups* [50]. For example, political deepfakes might be targeted to inflame existing social divides (affecting certain communities), and women have been disproportionately targeted by deepfake pornography – a heinous violation of privacy and dignity. These disparities highlight that solutions need to be inclusive and consider those most at risk (e.g. special support for victims of non-consensual deepfakes).

**Identity, Consent, and Representation:** The ethics of using AI-generated humans often revolves around questions of identity and consent. When is it acceptable to create a digital avatar or voice of someone? If that person is real, consent is paramount – yet there have been cases of deceased actors or public figures being "resurrected" via deepfake without clear consent (raising moral concerns about post-mortem rights and the wishes of the deceased/estate). Even for fictional or composite avatars, designers must be cautious not to unintentionally resemble a real individual too closely without permission. Culturally, notions of identity can also include group identity: for instance, portraying a member of a particular ethnic group in an AI-generated video might draw scrutiny if done by creators outside that group (issues of cultural appropriation). Ethical frameworks suggest that **respect for persons** (a principle from the Belmont Report) should extend to respecting a person's likeness and cultural identity. In practical terms, many researchers have their projects reviewed by Institutional Review Boards (IRBs) or ethics committees, especially when human likeness data (photos, voice recordings, biometric scans) are used. IRBs are increasingly grappling with AI-specific issues: the U.S. Office for Human Research Protections posed questions such as, "When AI research uses private identifiable information (like someone's images or voice), are those persons considered human subjects in need of consent?" [53]. The consensus is leaning toward a cautious approach: if AI research involves personal data (even publicly available images scraped from the internet), there could be ethical obligations to consider privacy and potential harms. For example, if a facial recognition dataset is built from online photos, those individuals may not know their faces are being used – an ethical review might require assessing this risk or seeking some form of community consent. Another IRB consideration is **bias and fairness**: committees may ask researchers how they addressed potential bias in an AI model (since an unfair algorithm could harm certain groups) [54]. This is a new frontier for IRBs, and scholars have proposed supplemental guidelines to ensure AI studies consider issues like bias, transparency, and impact on vulnerable groups [54].

**Biometric Data and Privacy:** Digital avatars typically rely on biometric data – facial scans, body measurements, voice prints – to create realistic representations. This raises privacy concerns because biometric data is highly sensitive. If leaked or misused, it could allow someone's identity to be stolen or an unauthorized deepfake to be made of them. Some jurisdictions (like the EU's GDPR) classify biometric data as a special category requiring explicit consent and purpose limitation. Researchers dealing with, say, a database of 3D face models must implement strong data protection (encryption, anonymization) and ensure participants know the risks. A theme in literature is the concept of **"virtual human" rights** – should individuals have rights to their digital likeness akin to image rights? For instance, if an AI company creates a very life-like avatar that coincidentally looks like a real person, should that person have any say or compensation? While laws lag behind, ethicists argue for clear consent procedures especially in studies that collect biometric information. Some have suggested watermarking datasets or results so that if an avatar or voice is synthetic, it can be identified (to prevent confusion with real identities). The deepfake study mentioned earlier advocated focusing on *privacy, consent, and transparency* as pillars of any ethical framework for AI media [55] [56]. Practically, that means obtaining consent when using someone's face or voice, informing users when they interact with an AI (e.g. a disclaimer if a video call is with an AI avatar instead of a human), and giving people control over their own biometric data.

**Ethical Use and Governance:** Researchers have proposed various ethical frameworks to guide development in this space. One approach is **Value Sensitive Design**, integrating human values (like autonomy, dignity, and diversity) from the earliest stages of technology design. Another is the **Ethics-as-a-Service** concept, where AI systems have built-in components that enforce ethical constraints (for example, an AI that refuses to generate content that violates someone's privacy or is overtly biased). On a higher level, industry and governments are issuing guidelines: the IEEE's *Ethically Aligned Design* and the EU's *AI Act* (forthcoming) both address issues of fairness, transparency, and accountability for AI. The literature on social implications often stresses *interdisciplinary collaboration*: technologists, ethicists, legal scholars, and community representatives should work together to foresee consequences and craft solutions [51]. For example, deepfake regulation benefits from technical input (on detection tools) and legal input (on crafting effective laws) and sociological input (on public education).

**Social Impact and Limitations:** On the positive side, some argue these same technologies (avatars, deepfakes) can be used for social good if done ethically – for instance, in entertainment, we might see more diverse representation through AI-generated characters; in education, a deepfake of a historical figure could provide an engaging lesson (with appropriate disclosure). In healthcare, as one ACM paper mused, deepfake tech could even personalize therapies (like creating a comforting avatar of a patient's relative for therapy) if handled carefully [57] [58]. These "pro-social deepfakes" illustrate the dual-use nature of the tech. Author-identified limitations in ethical research often mention the fast pace of AI development: policies and studies are always trying to catch up with new capabilities. There is also the challenge of measuring long-term effects – many studies are short-term or speculative. Experts unanimously call for ongoing vigilance: ethical guidelines should be revisited regularly, and a broad public dialogue is needed about what boundaries to set (which may differ culturally – for example, attitudes toward synthetic media and privacy can be stricter in Europe than in the U.S. or vary in Asia).

In conclusion, the emergence of AI-generated humans compels us to revisit fundamental questions of truth, identity, and respect. **Ensuring ethical practices** – from obtaining informed consent for using someone's likeness, to implementing bias checks, to safeguarding biometric data – is essential to prevent harm. The research community is actively contributing by highlighting risks (like deepfake harms [50]) and proposing solutions (like privacy-centric design [56]). The cross-cultural assessment angle reminds us that ethical norms are not uniform worldwide; hence, any cross-cultural research or deployment should engage local perspectives on what is acceptable and what isn't. By heeding these insights, the study of digital avatar performance and user acceptance can be grounded in not only technical excellence but also social responsibility, fostering technology that is innovative *and* inclusive, fair, and trustworthy.

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