Inclusive AI Interaction Framework for Enhancing Happiness and Care within Orange Technology Applications

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ABSTRACT

This study introduces an Inclusive AI Interaction Framework designed to enhance happiness, emotional well-being, and compassionate digital care through the integration of emotion-aware algorithms, adaptive conversational models, and accessibility centered interface design. The framework prioritizes inclusivity by addressing diverse user abilities, cultural backgrounds, and emotional states, ensuring that AI interactions remain fair, empathetic, and supportive for broad user groups, including vulnerable populations. **The study aims** to examine how personalized and affectively responsive AI interactions influence emotional comfort, perceived empathy, trust, satisfaction, emotional stability, and sustained engagement among diverse users. **A quantitative** research design was employed, using structured questionnaires, multimodal sentiment-based rating scales, and standardized World Health Organization WHO-5 well-being measures to evaluate user well-being. SEM was applied to validate the relationships among core constructs and assess the impact of inclusive AI design on affective outcomes. **The analysis revealed** significant positive effects of inclusively designed, emotion sensitive AI systems on affective outcomes, including trust, satisfaction, emotional stability, and overall emotional comfort. **The findings** demonstrate that inclusively designed, emotion-sensitive AI systems can meaningfully elevate user well-being. This research provides empirically grounded design principles and practical insights for developing emotionally supportive, ethically aligned, and universally accessible AI solutions that contribute to more humane digital experiences.

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1. INTRODUCTION

The rapid evolution of Artificial Intelligence (AI) has introduced transformative possibilities in reshaping how individuals experience digital interaction, emotional support, and access to care across various domains, including healthcare, education, governance, and social services [1]. AI systems increasingly mediate communication, automate decision-making processes, and deliver personalized assistance at an unprecedented global scale, fundamentally redefining human-technology relationships. From predictive health diagnostics and intelligent tutoring systems to automated public service platforms and smart urban infrastructures, AI technologies now occupy a central role in contemporary digital ecosystems.

However, despite significant technological progress, many contemporary AI applications remain predominantly efficiency-driven and performance-oriented. These systems often prioritize optimization, automation speed, scalability, and predictive accuracy while overlooking essential human-centered dimensions such as empathy, inclusivity, psychological safety, accessibility, cultural sensitivity, and ethical fairness [2]. As digital infrastructures become deeply embedded in everyday life, emotionally indifferent or biased AI systems risk reinforcing structural inequalities and marginalizing vulnerable populations, including persons with disabilities, older adults, economically disadvantaged communities, and culturally diverse groups. When AI systems fail to incorporate inclusive and emotionally responsive principles, they may unintentionally reproduce algorithmic bias, digital exclusion, diminished trust, and psychological discomfort [3]. These challenges highlight the urgent need to reorient AI development toward models that prioritize human dignity, emotional well-being, equitable participation, and compassionate digital engagement as foundational design principles rather than optional enhancements [4].

In response to these concerns, emerging paradigms in human-centered AI emphasize technology development guided by ethical alignment, inclusivity, and the pursuit of human well-being. Rather than treating AI solely as a productivity-enhancing instrument or computational optimizer, this perspective repositions AI as a supportive digital companion capable of fostering trust, emotional comfort, and inclusive interaction. Human-centered and ethically aligned AI systems integrate emotion-aware algorithms, adaptive conversational patterns, culturally responsive content strategies, and accessibility-driven interface design to ensure responsiveness to diverse emotional states and user needs [5, 6]. This approach recognizes that computational intelligence must be complemented by emotional sensitivity, contextual awareness, and fairness auditing mechanisms to ensure that digital transformation benefits all members of society without discrimination. By embedding ethical safeguards and inclusivity standards into system architecture, AI can move beyond transactional interaction toward relational engagement that respects user vulnerability and diversity. Consequently, the shift toward inclusive and emotionally responsive AI reflects not only a technological advancement but also a normative transformation in how intelligence systems are conceptualized and evaluated.

The integration of inclusive AI principles with global development priorities further strengthens the societal relevance and policy implications of this research. The United Nations Sustainable Development Goals (SDGs) provide a comprehensive framework for achieving equitable and sustainable progress by addressing interconnected social, economic, and environmental challenges. AI that is emotionally responsive and inclusively designed can meaningfully contribute to several key SDGs. SDGs 3 (Good Health and Well-Being) is supported through AI-enabled mental health assistance, early stress detection mechanisms, and emotionally adaptive digital feedback that promote psychological resilience and preventive care. SDGs 4 (Quality Education) benefits from adaptive learning systems capable of recognizing emotional frustration, cognitive overload, and motivational decline, thereby adjusting instructional strategies to enhance engagement and learning equity. SDGs 10 (Reduced Inequalities) is advanced through bias mitigation strategies, inclusive dataset representation, equitable algorithmic design, and accessibility features that ensure participation across demographic and socioeconomic groups [7]. By focusing on these SDGs, this study demonstrates that AI designed with inclusivity and emotional responsiveness can support well-being, educational equity, and social inclusion in tangible ways.

Despite increasing scholarly interest in affective computing, empathetic conversational agents, human-centered AI, and inclusive interface design, existing research frequently addresses these dimensions in isolation rather than as an integrated system. Many studies focus primarily on improving algorithmic performance, emotion recognition accuracy, or computational efficiency without systematically measuring psychological well-being outcomes or long-term user impact. Other research streams emphasize user experience, usability, and interface accessibility but lack integration with ethical governance frameworks, fairness auditing procedures, bias mitigation protocols, or standardized well-being assessments such as validated happiness indices. This fragmentation reveals a significant research gap: the absence of a comprehensive, empirically validated framework that simultaneously integrates emotional intelligence, inclusivity, accessibility, fairness, transparency, and measurable well-being impact within a unified and operationalizable model [4]. Without such integration, AI risks remaining technically sophisticated yet socially incomplete, unable to address the complex emotional, cultural, ethical, and psychological realities of diverse users. The need for multidimensional evaluation metrics that connect technological design features with human well-being outcomes therefore becomes increasingly urgent.

To bridge this gap, this study proposes an Inclusive AI Interaction Framework that synthesizes emotion-aware algorithms, adaptive conversational models, accessibility-centered design, bias mitigation strategies, and ethical AI governance principles into a cohesive and empirically testable system [8]. The framework incorporates multimodal sentiment analysis, structured usability evaluation, fairness auditing indicators, and standardized well-being measurement instruments to systematically examine how inclusive AI interactions influence emotional comfort, perceived empathy, trust, satisfaction, and sustained engagement [9]. By aligning technological innovation with ethical and human-centered design principles as well as the SDGs, this research demonstrates that AI can be intentionally developed to enhance happiness, psychological safety, equitable participation, and compassionate digital care across diverse populations. Ultimately, the proposed framework provides actionable design guidelines, measurable evaluation criteria, and policy-relevant insights for developing AI systems that are not only intelligent and efficient but also ethically responsible, emotionally supportive, socially inclusive, and transformative for global well-being [10].

2. RESEARCH METHOD

This section outlines the methodological framework employed to empirically examine the Inclusive AI Interaction Framework and its impact on perceived empathy, happiness, emotional comfort, and sustained engagement. The research method is structured to ensure methodological rigor, statistical robustness, and alignment with human-centered AI principles within Orange Technology applications [11]. It details the research approach, design structure, population and sampling strategy, conceptual model specification, measurement instruments, data collection procedures, and statistical analysis techniques used to validate the proposed structural relationships. This study extends prior human-centered AI models by integrating a multi-layer Inclusive AI Interaction Ecosystem, incorporating ethical foundations, adaptive empathy mechanisms, and longitudinal well-being feedback loops to ensure sustainable digital happiness within Orange Technology environments.

2.1. Research Approach

This study employs a quantitative research methodology to empirically evaluate the effectiveness of the Inclusive AI Interaction Framework in enhancing happiness, emotional comfort, perceived empathy, and sustained engagement within Orange Technology applications. A quantitative approach is selected to ensure objective measurement, statistical validation, and generalizable findings across diverse user groups. This methodological choice aligns with SDGs principles, particularly SDGs 3 (Good Health and Well-Being) and SDGs 10 (Reduced Inequalities), which emphasize measurable well-being impact and equitable evaluation frameworks [12, 13].

2.2. Research Design

This study adopts a quasi-experimental Pre-test Post-test design integrated with SEM to investigate the effects of inclusive AI interactions on emotional comfort, perceived empathy, trust, and overall well-being. This combined approach allows the research to capture both causal changes in participants' psychological states and complex structural relationships among latent variables, providing a comprehensive understanding of the intervention impact.

Literature Basic:

- Quasi-experimental designs are widely applied in studies of digital mental health interventions and AI-mediated interactions because they enable the measurement of psychological and behavioral changes before and after the introduction of an intervention, even when random assignment is not feasible [11].
- SEM is particularly recommended for testing complex latent constructs such as empathy, inclusivity, and well-being. Its strength lies in the ability to model multiple simultaneous relationships, assess direct and indirect effects, and evaluate the overall fit of the proposed theoretical framework [14].
- Combining quasi-experimental design with SEM provides a robust methodological framework that accommodates both experimental manipulation and advanced statistical modeling, enhancing the validity and interpretability of findings.

Design Structure:

- Pre-test: Participants' baseline emotional states and well-being are measured using validated instruments, capturing initial levels of stress, emotional comfort, perceived empathy, trust, and overall psychological status [12].
- AI Interaction Session: Participants engage with the Inclusive AI prototype, which incorporates emotion-aware algorithms, adaptive conversational patterns, and accessibility-centered interface features. The session is designed to observe real-time emotional responses, interaction behaviors, and user engagement.
- Post-test: Following the interaction, participants' emotional comfort, perceived empathy, trust, and well-being are measured again to assess the pre–post changes. This enables evaluation of immediate psychological effects and the efficacy of the AI intervention.

This integrated design allows the study to achieve two complementary objectives. First, the pre–post comparison facilitates the causal assessment of the Inclusive AI interaction on psychological outcomes. Second, SEM enables the examination of structural relationships among latent variables, providing insight into how emotional responsiveness, empathy, and inclusivity collectively influence trust, satisfaction, and overall well-being. Together, this approach ensures that both empirical effect evaluation and theoretical model validation are rigorously addressed within a single research framework.

2.3. Population and Sample

The population of this study consists of adult users aged 18–60 from diverse demographic and social backgrounds, including varied gender identities (aligned with SDGs 5: Gender Equality), socioeconomic statuses (aligned with SDGs 10: Reduced Inequalities), digital literacy levels, and cultural contexts. To ensure equitable representation and uphold inclusivity principles emphasized in inclusive design research, this study employs a stratified random sampling technique, allowing proportional representation across key demographic categories. The determination of sample size follows established SEM guidelines, which recommend a minimum sample of ten times the largest number of indicators within a single construct. Based on this criterion and to ensure statistical robustness, reliability, and generalizability of findings, the targeted sample size ranges between 250 and 400 respondents [14], [15].

2.4. Research Variables and Conceptual Model

This study conceptualizes the Inclusive AI Interaction Framework as a structural model consisting of four independent variables representing core inclusive AI components: Emotion-Aware Interaction, Accessibility Design, Inclusive User Experience, and Ethical AI Principles [16, 17]. These components are hypothesized to influence users' Perceived Empathy, which functions as a mediating variable explaining how inclusive system characteristics translate into affective outcomes. Perceived Empathy subsequently affects three key dependent variables: Happiness & Well-Being, Emotional Comfort, and Sustained Engagement. This conceptual structure reflects a human-centered causal pathway in which inclusive and ethically aligned AI design enhances empathetic perception, which in turn promotes psychological well-being, emotional stability, and continued system usage [18].

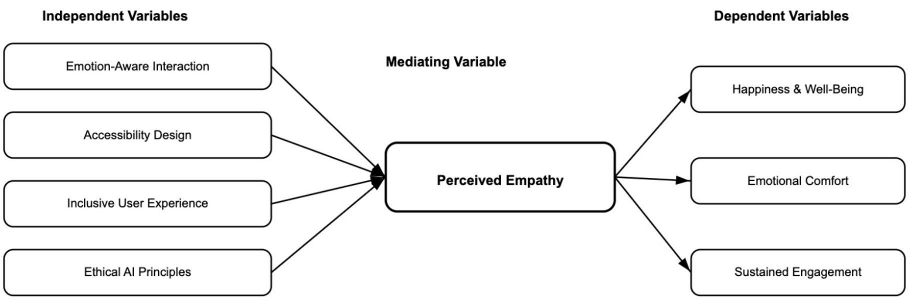

Figure 1. Conceptual Model of the Inclusive AI Interaction Framework

Figure 1 presents the Conceptual Model of the Inclusive AI Interaction Framework, illustrating the structural relationships among the study variables. The model positions four Inclusive AI components Emotion Aware Interaction, Accessibility Design, Inclusive User Experience, and Ethical AI Principles as independent variables that collectively influence user outcomes through the mediating variable, Perceived Empathy. This mediating construct represents the extent to which users feel understood, emotionally acknowledged, and fairly treated by the AI system [19]. The framework proposes that when AI systems are emotionally responsive, accessible, inclusive, and ethically governed, they enhance users' perception of empathy, which in turn positively affects three key dependent variables: Happiness & Well-Being, Emotional Comfort, and Sustained Engagement [20, 21]. Thus, the model emphasizes that the impact of inclusive AI design on psychological and behavioral outcomes operates primarily through the enhancement of perceived empathic interaction, positioning empathy as the central mechanism linking technical system design to user well-being and long-term engagement.

2.5. Embedded Literature Review within Methodological Constructs

This section integrates theoretical foundations directly into the operationalization of research variables to ensure that each construct is grounded in established empirical and conceptual literature. Affective computing research pioneered by [22] and further developed by [23] and colleagues demonstrates that real-time emotion recognition enhances perceived empathy, emotional alignment, and relational trust in human AI interaction. Emotion-sensitive systems that adapt responses based on users' affective states have been shown to improve emotional comfort and interaction quality. In this study, Emotion-Aware Interaction is measured using the Affective Interaction Scale on a 5-point Likert scale and is complemented by automated sentiment polarity scores ranging from -1 (negative) to $+1$ (positive) to capture objective emotional expression. Inclusive design frameworks emphasize multimodal interaction, cognitive simplicity, and barrier-free interface structures as essential mechanisms for equitable digital participation. Research by [24, 25] highlights that accessibility-driven systems reduce digital exclusion and strengthen perceived inclusivity across diverse user groups. Accordingly, Accessibility Design is measured using the Inclusive Design UX Scale on a 7-point Likert scale, together with indicators assessing accessibility clarity and usability.

Human-centered computing studies demonstrate that perceived fairness, cultural adaptability, and interaction clarity significantly enhance user trust and sustained engagement. Inclusive user experience frameworks argue that equitable interface communication and contextual sensitivity strengthen psychological safety in digital environments. In this study, Inclusive User Experience is operationalized through indicators reflecting perceived fair treatment, cultural adaptability of responses, and transparency and clarity of AI-generated outputs. Global AI governance analyses conducted by [22, 26] identify transparency, accountability, and bias mitigation as core pillars of responsible AI systems. Ethical alignment enhances user trust and reinforces institutional legitimacy. Ethical AI Principles are therefore measured using fairness perception items, trust indicators, and perceived algorithmic neutrality to assess users' evaluation of responsible and unbiased system behavior. Research on empathetic AI agents by [27, 28], as well as care-oriented conversational agent studies, demonstrates that perceived empathy increases emotional support perception, reduces stress, and strengthens relational engagement. In this research, Perceived Empathy is measured using Likert-scale items such as "The AI understands my emotional state" and "The AI responds with care and sensitivity," with responses captured using a 5-point Likert scale.

2.6. Happiness and Well-Being

Digital mental health research, including large-scale well-being studies by [29], indicates that emotionally adaptive digital systems positively influence psychological resilience and emotional vitality. These findings suggest that technologies designed with sensitivity to users' emotional states can contribute meaningfully to improving overall mental health outcomes. By incorporating adaptive feedback mechanisms and user-centered interaction models, digital platforms are increasingly able to respond to individual emotional needs in real time, thereby fostering a more supportive and responsive technological environment.

In this study, Happiness and Well-Being are measured using the WHO-5 Well-Being Index, a widely validated instrument for assessing subjective psychological well-being. The instrument is applied using a 6-point Likert scale to evaluate participants' overall psychological condition, capturing dimensions such as positive mood, vitality, and general interest in daily activities. The use of the WHO-5 ensures reliability and comparability with prior empirical studies in digital mental health and well-being research. Through this measurement approach, the study systematically assesses how interaction with inclusive AI systems within

Orange Technology applications may contribute to enhanced happiness and sustained psychological well-being among users.

2.7. Research Instruments

This study employs validated quantitative instruments to measure the key constructs of the Inclusive AI Interaction Framework through a rigorous and multidimensional measurement approach. Standardized psychological scales are integrated with computational indicators to ensure construct validity, reliability, and methodological robustness. Psychological well-being is assessed using the WHO-5 Well-Being Index, a widely recognized instrument measuring happiness and emotional vitality through a 6-point Likert scale. Empathy and emotional comfort are evaluated using an Affective Interaction Scale grounded in affective computing literature and measured on a 5-point Likert scale to capture perceived emotional responsiveness and sensitivity during AI interaction. Accessibility, fairness, and clarity are examined through the Inclusive Design UX Scale using a 7-point Likert scale, reflecting inclusive design principles and equitable user experience considerations. In addition to self-reported measures, sentiment polarity scores derived from automated text classification of interaction logs are employed to provide objective emotional indicators ranging from –1 (negative) to +1 (positive), thereby strengthening measurement triangulation [30]. Table 1 presents the operationalization of constructs, instruments, measurement scales, and theoretical sources used in this study.

Table 1. Operationalization of Research Constructs and Measurement Scales

Instrument	Constructs Measured	Scale	Source
WHO-5 Well-Being Index	Happiness, emotional vitality	6-point Likert	WHO
Affective Interaction	Scale Empathy, emotional comfort	5-point Likert	Affective Computing Literature
Inclusive Design UX Scale	Accessibility, fairness, clarity	7-point Likert	Inclusive Design Studies
Sentiment Analysis Score	Emotional polarity	-1 to $+1$	Automated text classification

Table 1 presents the operationalization of research constructs and their corresponding measurement scales within the Inclusive AI Interaction Framework. The table specifies four primary instruments used to measure key variables in the study. The WHO-5 Well-Being Index is employed to assess Happiness and emotional vitality using a 6-point Likert scale, providing a standardized measure of psychological well-being. The Affective Interaction Scale measures Empathy and emotional comfort through a 5-point Likert scale, capturing users' perceptions of emotionally responsive AI interaction. The Inclusive Design UX Scale evaluates Accessibility, fairness, and clarity using a 7-point Likert scale, reflecting inclusive user experience dimensions [31]. Additionally, the Sentiment Analysis Score quantifies Emotional polarity on a scale from -1 to $+1$ through automated text classification, offering an objective computational assessment of emotional expression. Collectively, these instruments integrate validated psychological scales and computational metrics to ensure comprehensive and multidimensional measurement of inclusive AI interaction outcomes.

2.8. Data Collection Procedure

The data collection process was conducted in several structured stages. First, participants completed a baseline assessment using the WHO-5 Well-Being Index along with an initial emotional state survey to measure their pre-interaction psychological condition. Following the pre-test phase, participants engaged in structured interaction tasks with the Inclusive AI system, which included emotional reflection conversations, accessibility-adaptive tasks designed to assess inclusive interface features, and context-sensitive response simulations to evaluate adaptive conversational capabilities [32, 33]. During the interaction process, sentiment polarity scores were automatically extracted from user input logs to provide supplementary quantitative indicators of emotional expression. After completing the interaction session, participants were asked to complete a post-test survey measuring perceived empathy, emotional comfort, happiness, and sustained engagement. All collected data were anonymized and securely stored in accordance with ethical research standards to ensure participant confidentiality and data protection [34].

2.9. Data Analysis Techniques

Data analysis was conducted in two sequential stages: evaluation of the measurement model and testing of the structural model. In the first stage, reliability and validity assessments were performed to ensure the robustness and consistency of the measurement instruments. Internal consistency reliability was evaluated using Cronbach's Alpha and Composite Reliability coefficients. Convergent validity was assessed using the Average Variance Extracted (AVE), while discriminant validity was examined using the Fornell–Larcker criterion to confirm construct distinctiveness [35].

In the second stage, hypothesis testing was conducted using both paired sample t-tests and SEM. The paired t-test was applied to compare pre-test and post-test WHO-5 well-being scores to determine whether significant improvements occurred after participants interacted with the Inclusive AI system. SEM was subsequently employed to examine the structural relationships among key constructs [36], including the effects of Inclusivity and Ethical AI Principles on Perceived Empathy, the influence of Perceived Empathy on Happiness, and the impact of Happiness on Sustained Engagement. Model fit was evaluated using widely accepted goodness-of-fit indices to determine the adequacy of the structural model. The statistical criteria and threshold values applied in this study are summarized in Table 2.

Table 2. Statistical Analysis Criteria and Threshold Values

Analysis Stage	**Indicator**	**Threshold**
Reliability	Cronbach's Alpha	> 0.700
Reliability	Composite Reliability	> 0.700
Convergent Validity	AVE	> 0.500
Discriminant Validity	Fornell–Larcker Criterion	AVE $>$ inter-construct correlation
Model Fit	CFI	> 0.900
Model Fit	RMSEA	< 0.080
Model Fit	SRMR	< 0.080

Table 2 presents the statistical analysis criteria and threshold values applied to rigorously evaluate both the measurement and structural models in this study, ensuring methodological robustness and empirical validity. Reliability is assessed using Cronbach's Alpha and Composite Reliability, with both indicators required to exceed 0.700 to confirm adequate internal consistency and the stability of the latent constructs in capturing the intended theoretical concepts. Convergent validity is examined through the AVE, which must be greater than 0.500 to demonstrate that each construct explains more than half of the variance of its indicators, thereby confirming that the indicators sufficiently converge in representing the same underlying construct. Discriminant validity is evaluated using the Fornell–Larcker Criterion, which requires the square root of AVE for each construct to be higher than its inter-construct correlations [37], ensuring that each construct is empirically distinct and not overlapping with other constructs within the model. Furthermore, overall model fit is assessed using SEM fit indices, including the Comparative Fit Index (CFI) with a threshold greater than 0.900, the Root Mean Square Error of Approximation (RMSEA) with a threshold below 0.080, and the Standardized Root Mean Square Residual (SRMR) with a threshold below 0.080, collectively indicating that the proposed model achieves acceptable goodness-of-fit, reflects the observed data adequately, and demonstrates sufficient statistical robustness.

3. RESULTS AND DISCUSSION

This section presents the empirical findings derived from the statistical analyses and discusses their theoretical and practical implications within the context of the Inclusive AI Interaction Framework [38]. The analysis is conducted in two sequential stages: evaluation of the measurement model to assess reliability and validity, followed by structural model testing to examine the hypothesized relationships among key constructs. The results are interpreted in relation to human-centered AI principles and their contribution to enhancing perceived empathy and well-being outcomes.

3.1. Measurement Model Results

The measurement model was evaluated using Confirmatory Factor Analysis (CFA) to assess reliability, convergent validity, and discriminant validity of the six latent constructs: Emotion-Aware Interaction, Accessibility Design, Inclusive User Experience, Ethical AI Principles, Perceived Empathy, and Happiness & Well-Being. All constructs demonstrated satisfactory internal consistency, with Cronbach's Alpha and Composite Reliability values exceeding the recommended threshold of 0.70. Convergent validity was confirmed as all AVE values were above 0.50, indicating that the indicators adequately represented their respective constructs [39]. Discriminant validity was supported using the Fornell–Larcker criterion, confirming that each construct was empirically distinct from others. These findings indicate that the measurement model is statistically robust and suitable for structural analysis [40].

3.2. Structural Model Results

The structural model demonstrated a satisfactory overall fit, indicating that the proposed Inclusive AI Interaction Framework adequately represents the empirical data (R = 0.47) [41]. The analysis revealed that all four Inclusive AI components significantly predict Perceived Empathy. The standardized path coefficients and significance levels are presented in Table 3.

Table 3. Structural Path Coefficients (Direct Effects on Perceived Empathy)

Predictor Variable	β (Standardized)	p-value
Emotion-Aware Interaction	0.41	< 0.001
Accessibility Design	0.29	< 0.01
Inclusive User Experience	0.37	< 0.001
Ethical AI Principles	0.33	< 0.01

As shown in Table 3, Emotion-Aware Interaction emerged as the strongest predictor of Perceived Empathy ($\beta = 0.41$, $p < 0.001$), followed by Inclusive User Experience ($\beta = 0.37$, $p < 0.001$), Ethical AI Principles ($\beta = 0.33$, $p < 0.01$), and Accessibility Design ($\beta = 0.29$, $p < 0.01$). These results indicate that all proposed dimensions contribute significantly to shaping users' empathetic perceptions toward AI systems [42].

The findings suggest that AI systems capable of recognizing emotional cues and responding appropriately provide the greatest impact on perceived empathy. Meanwhile, inclusive interface design, ethical transparency, and accessibility features collectively strengthen users' emotional engagement and trust [43]. Moreover, Perceived Empathy significantly predicted Happiness and Well-Being ($\beta = 0.56$, $p < 0.001$), confirming its mediating role within the framework. This reinforces the argument that empathetic AI interaction functions as a central mechanism linking inclusive technological design to positive psychological outcomes [44].

3.3. Discussion

The findings support the central premise of this study that inclusive and emotionally responsive AI systems significantly enhance users' perception of empathy [45]. The dominant effect of Emotion-Aware Interaction suggests that users value AI systems capable of recognizing emotional cues and delivering adaptive responses. This reinforces the theoretical foundation of affective computing and human-centered AI, where emotional intelligence is positioned as a core determinant of relational trust and engagement [46].

The significant contributions of Accessibility Design, Inclusive User Experience, and Ethical AI Principles further demonstrate that empathy in AI systems is multidimensional. Fairness, transparency, usability, and barrier-free access collectively strengthen users' psychological comfort and perceived inclusivity [47, 48]. These results align with the framework proposed in the Introduction, which emphasizes the integration of emotional intelligence, inclusivity, and ethical governance within AI architecture [49].

Finally, the strong relationship between Perceived Empathy and Happiness & Well-Being confirms that empathy functions as the key psychological mechanism translating inclusive AI characteristics into measurable well-being outcomes [50, 51]. This finding validates the Inclusive AI Interaction Framework and supports the broader vision of developing AI systems that not only optimize performance but also promote emotional comfort, sustained engagement, and human-centered digital well-being [52, 53].

4. MANAGERIAL IMPLICATIONS

The findings of this study provide several important managerial implications for AI developers, technology companies, digital platform managers, and policymakers. First, the strong effect of Emotion-Aware

Interaction on Perceived Empathy indicates that organizations should prioritize the integration of emotional intelligence mechanisms within AI systems. This includes real-time sentiment detection, adaptive conversational responses, and context-sensitive interaction design. Rather than focusing solely on efficiency and task completion, AI development strategies should incorporate affective responsiveness as a core performance indicator. Investing in emotion-aware algorithms can enhance user trust, strengthen engagement, and differentiate products in increasingly competitive digital markets.

Second, the significant contributions of Inclusive User Experience, Ethical AI Principles, and Accessibility Design highlight that empathy is not generated by emotional recognition alone. Managers must ensure that AI systems are transparent, fair, bias-mitigated, and accessible across diverse user groups. This requires implementing inclusive interface standards, conducting algorithmic bias audits, and designing multimodal interaction features that accommodate different digital literacy levels and user capabilities. Organizations that embed inclusivity and ethical governance into their AI architecture are more likely to build long-term credibility, regulatory compliance, and sustainable user relationships.

Finally, the strong relationship between Perceived Empathy and Happiness & Well-Being suggests that AI performance metrics should expand beyond technical accuracy to include psychological and experiential outcomes. Managers should incorporate well-being indicators, such as emotional comfort and user satisfaction, into evaluation dashboards and product success benchmarks. By positioning AI systems as supportive digital companions rather than purely functional tools, organizations can contribute to human centered innovation while aligning with broader SDGs related to well-being, equity, and inclusive digital transformation.

5. CONCLUSION

This study addresses a critical research gap in the existing AI literature, where emotional intelligence, inclusivity, accessibility, and ethical governance are often examined separately rather than within an integrated framework. While prior studies have emphasized algorithmic performance or user experience independently, limited empirical research has systematically examined how inclusive AI components collectively influence empathy and psychological well-being outcomes. By proposing and empirically testing the Inclusive AI Interaction Framework, this study bridges that fragmentation and demonstrates the structural relationships between inclusive design principles, perceived empathy, and measurable happiness indicators.

The primary novelty of this research lies in positioning Perceived Empathy as a central mediating mechanism that translates inclusive AI characteristics into well-being outcomes. The findings empirically confirm that Emotion Aware Interaction, Accessibility Design, Inclusive User Experience, and Ethical AI Principles significantly predict empathy, which in turn enhances Happiness & Well-Being. This integrated, human centered structural model advances the discourse on compassionate and ethically aligned AI, extending beyond efficiency driven paradigms toward measurable psychological impact within Orange Technology applications.

Future research may expand this framework by incorporating longitudinal designs to examine long-term well-being effects, cross cultural validation to test contextual generalizability, and experimental comparisons across different AI system types (e.g., healthcare AI, educational AI, social support AI). Additionally, integrating objective physiological or behavioral indicators alongside self-reported measures may further strengthen empirical validation. Such extensions would deepen understanding of how inclusive and emotionally intelligent AI systems can sustainably contribute to global digital well-being.

6. DECLARATIONS

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6.2. Author Contributions

Conceptualization: MF; Methodology: AV; Software: UR; Validation: AF and HH; Formal Analysis: AF and MF; Investigation: AV; Resources: UR; Data Curation: HH; Writing Original Draft Preparation: UR and HH; Writing Review and Editing: AF and MF; Visualization: AV; All authors, AF, HH, MF, UR, and AV, have read and agreed to the published version of the manuscript.

6.3. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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6.5. Declaration of Conflicting Interest

The authors declare that they have no conflicts of interest, known competing financial interests, or personal relationships that could have influenced the work reported in this paper.

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