



Original-Forschungsarbeit

Künstliche Intelligenz und zwischenmenschliche Beziehungen im Iran: Kulturelle und soziale Herausforderungen

Shahnaz Khademizadeh¹, Sam Clarke^{2*}, Zeinab Mohammadi³

¹ Professorin für Wissens- und Informationswissenschaft, Shahid-Chamran-Universität Ahwaz, Ahwaz, Iran

² Dozent für Primarstufen-Lehrerbildung (Primary ITE), York St John University, York, Vereinigtes Königreich

³ Promotion in Wissens- und Informationswissenschaft, Shahid-Chamran-Universität Ahwaz, Ahwaz, Iran

Empfangen: 10. März 2025 Akzeptiert: 9. Juni 2025

Zusammenfassung:

Diese Studie untersucht die vielschichtigen Auswirkungen der Künstlichen Intelligenz (KI) auf zwischenmenschliche Beziehungen in der iranischen Gesellschaft und hebt die kulturellen, sozialen und psychologischen Herausforderungen hervor, die mit der raschen Verbreitung von KI-Technologien einhergehen. Mit der zunehmenden Integration von Instrumenten wie virtuellen Assistenten, Social-Media-Algorithmen und KI-gestützten Kommunikationsplattformen in den Alltag verändern sich Interaktionsmuster, emotionale Bindungen und kulturelle Normen grundlegend. Die Untersuchung basiert auf zwölf halbstrukturierten Interviews und folgt einem Mixed-Methods-Ansatz mit qualitativer Schwerpunktsetzung, einschließlich thematischer Analyse, Überprüfung der Intercoder-Reliabilität und fallübergreifender Vergleichsanalyse. Die Ergebnisse zeigen eine doppelte Dynamik: Einerseits fördert KI Kommunikation, Produktivität und alltägliche Effizienz; andererseits schwächt sie direkte Face-to-Face-Interaktionen, emotionale Bindungen und traditionelle soziale Praktiken, die zentral für die iranische Kultur sind. Die Befunde weisen auf zunehmende Sorgen hinsichtlich geschwächter familiärer und gemeinschaftlicher Bindungen, abnehmender sozialer Kompetenzen, wachsender Abhängigkeit von intelligenten Systemen sowie generationsbedingter Unterschiede in der digitalen Anpassung hin. Darüber hinaus berichten die Teilnehmenden von breiteren kulturellen Veränderungen, darunter der Aufstieg virtueller Lebensstile, Bedrohungen der kulturellen Identität und eine wachsende soziale Ungleichheit infolge ungleicher Zugänge zu KI-Technologien. Die Studie identifiziert zudem psychologische Risiken wie Einsamkeit, oberflächliche Online-Verbindungen, verminderte Empathie und den Rückgang emotionaler Intelligenz im Zuge zunehmender Interaktionen mit algorithmischen Systemen. Auf gesellschaftlicher Ebene erzeugen Fragen des Datenschutzes, der Daten-Governance und ethischer Regulierung zusätzlichen Druck, der das öffentliche Vertrauen und die Dynamik zwischenmenschlicher Beziehungen beeinflusst. Die Untersuchung leistet einen Beitrag zu nationalen und internationalen Debatten über Mensch-KI-Interaktion, indem sie aufzeigt, wie globale Technologien mit lokalen kulturellen Kontexten interagieren. Sie argumentiert, dass ein ausgewogenes Verhältnis zwischen technologischer Innovation und der Bewahrung iranischer sozialer Werte entscheidend ist, damit KI die Grundlagen bedeutungsvoller menschlicher Beziehungen stärkt, anstatt sie zu untergraben.

Schlüsselwörter: künstliche Intelligenz, zwischenmenschliche Beziehungen, kulturelle Herausforderungen, soziale Dynamiken, iranische Gesellschaft

* Korrespondierender Autor

✉ s.clarke1@yorksj.ac.uk

🌐 <https://orcid.org/0009-0000-9297-3835>

Wie dieser Artikel zu zitieren ist:

Khademizadeh, Sh., Clarke, S., & Mohammadi, Z. (2025). AI and interpersonal relationships in Iran: Cultural and social challenges. *Spektrum Iran*, 38(2), 83-113.

🔗 <https://doi.org/10.22034/spektrum.2026.554746.1043>

© Copyright © Der/die Autor(en); Dieses Werk ist lizenziert unter einer Creative Commons Namensnennung - Nicht kommerziell - Keine Bearbeitungen 4.0 International (CC-BY-NC) Lizenz. Homepage: www.spektrumiran.com

هوش مصنوعی و روابط بین فردی در ایران: چالش‌های فرهنگی و اجتماعی

شهناز خادمی‌زاده^۱، سم کلارک^{۲*}، زینب محمدی^۳

^۱استاد علم اطلاعات و دانش‌شناسی، دانشگاه شهید چمران اهواز، اهواز، ایران

^۲مدرس تربیت معلم ابتدایی (ITE)، دانشگاه یورک سنت جان، یورک، بریتانیا

^۳دکتری علم اطلاعات و دانش‌شناسی، دانشگاه شهید چمران اهواز، اهواز، ایران

دریافت: ۱۴۰۳/۱۲/۲۰؛ پذیرش: ۱۴۰۴/۰۳/۱۹

چکیده:

این پژوهش به بررسی تأثیرات چندوجهی هوش مصنوعی (AI) بر روابط بین فردی در جامعه ایران می‌پردازد و چالش‌های فرهنگی، اجتماعی و روان‌شناختی ناشی از گسترش سریع فناوری‌های مبتنی بر هوش مصنوعی را برجسته می‌کند. با نهادینه‌شدن ابزارهایی همچون دستیارهای مجازی، الگوریتم‌های شبکه‌های اجتماعی و پلتفرم‌های ارتباطی مبتنی بر هوش مصنوعی در زندگی روزمره، الگوهای تعامل، درگیری عاطفی و هنجارهای فرهنگی در حال دگرگونی هستند. این پژوهش بر پایه دوازده مصاحبه نیمه‌ساختاریافته و با رویکردی ترکیبی با غلبه کیفی انجام شده است که شامل تحلیل مضمون، سنجش پایایی میان‌گذازان و مقایسه میان‌موردی می‌شود. یافته‌ها روایتی دوگانه را نشان می‌دهد: از یک سو، هوش مصنوعی ارتباطات، بهره‌وری و سهولت امور روزمره را تقویت می‌کند؛ و از سوی دیگر، تعاملات چهره‌به‌چهره، پیوندهای عاطفی و شیوه‌های سنتی اجتماعی ریشه‌دار در فرهنگ ایرانی را تضعیف می‌سازد. نتایج بیانگر نگرانی‌های فزاینده درباره تضعیف روابط خانوادگی و اجتماعی، کاهش مهارت‌های اجتماعی، وابستگی به سامانه‌های هوشمند و شکاف نسلی در سازگاری دیجیتال است. مشارکت‌کنندگان همچنین به دگرگونی‌های گسترده فرهنگی، از جمله گسترش سبک زندگی مجازی، تهدید هویت فرهنگی و افزایش نابرابری اجتماعی ناشی از دسترسی نابرابر به ابزارهای هوش مصنوعی اشاره کردند. این مطالعه افزون بر این، مخاطرات روان‌شناختی همچون احساس تنهایی، ارتباطات سطحی آنلاین، کاهش همدلی و افت هوش هیجانی را در پی تعامل روزافزون افراد با سامانه‌های الگوریتمی شناسایی می‌کند. در سطح کلان اجتماعی نیز مسائل مربوط به حریم خصوصی، حکمرانی داده و چالش‌های اخلاقی، فشارهای مضاعفی ایجاد می‌کند که بر اعتماد عمومی و پویایی روابط اثرگذار است. این پژوهش با نشان دادن چگونگی تعامل فناوری‌های جهانی با بسترهای فرهنگی محلی، به مباحث ملی و بین‌المللی درباره تعامل انسان و هوش مصنوعی کمک می‌کند. در نهایت، تأکید می‌شود که ایجاد توازن میان نوآوری فناورانه و حفظ ارزش‌های اجتماعی ایرانی برای تضمین آن ضروری است که هوش مصنوعی به جای تضعیف، بنیان‌های روابط انسانی معنادار را تقویت کند.

واژگان کلیدی: هوش مصنوعی، روابط بین فردی، چالش‌های فرهنگی، پویایی‌های اجتماعی، جامعه ایرانی



Original Research Paper

AI and interpersonal relationships in Iran: Cultural and social challenges

Shahnaz Khademizadeh¹, Sam Clarke^{2*}, Zeinab Mohammadi³

¹ Professor of Knowledge & Information Science, Shahid Chamran University of Ahwaz, Ahwaz, Iran

² Lecturer of Primary ITE, York St John University, York, UK

³ PhD in Knowledge and Information, Shahid Chamran University of Ahwaz, Ahwaz, Iran

Received: Mar. 10, 2025 Accepted: Jun. 09, 2025

Abstract

This study examines the multifaceted impact of artificial intelligence (AI) on interpersonal relationships within Iranian society, highlighting the cultural, social, and psychological challenges emerging from the rapid adoption of AI technologies. As tools such as virtual assistants, social media algorithms, and AI-driven communication platforms become embedded in daily life, they are reshaping patterns of interaction, emotional engagement, and cultural norms. Drawing on twelve semi-structured interviews analyzed through a qualitative-dominant mixed-methods approach, including thematic analysis, intercoder reliability checks, and cross-case comparison, the research identifies a dual narrative: AI enhances communication, productivity, and daily convenience, yet simultaneously undermines face-to-face engagement, emotional bonds, and traditional social practices central to Iranian culture. Findings reveal growing concerns about weakened family and community ties, reduced social skills, dependency on intelligent systems, and generational gaps in digital adaptation. Participants also noted broader cultural shifts, including the rise of virtual lifestyles, threats to cultural identity, and increased social inequality driven by uneven access to AI tools. The study further identifies psychological risks such as loneliness, superficial online connections, diminished empathy, and the perceived decline of emotional intelligence as individuals increasingly interact with algorithmic systems. At the societal level, privacy, data governance, and ethical challenges create additional pressures that shape public trust and relational dynamics. The study contributes to national and international debates on human-AI interaction by demonstrating how global technologies interact with local cultural contexts. It argues that balancing technological innovation with the preservation of Iranian social values is essential to ensuring that AI strengthens rather than erodes the foundations of meaningful human relationships.

Keywords: artificial intelligence, interpersonal relationships, cultural challenges, social dynamics, Iranian society

* Corresponding Author

✉ s.clarke1@yorks.ac.uk

🌐 <https://orcid.org/0009-0000-9297-3835>

How to Cite this Article:

Khademizadeh, Sh., Clarke, S., & Mohammadi, Z. (2025). AI and interpersonal relationships in Iran: Cultural and social challenges. *Spektrum Iran*, 38(2), 83-113.

🔗 <https://doi.org/10.22034/spektrum.2026.554746.1043>

© Copyright © The Author(s); This work is licensed under a Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International (CC-BY-NC) License. Homepage: www.spektrumiran.com

1. Introduction

In recent years, artificial intelligence (AI) has become deeply embedded in everyday life, with more than 55% of the global population regularly interacting with AI technologies. The global AI market, valued at approximately US\$454.12 billion (AIRPM, 2024), includes tools such as virtual assistants, social media algorithms, and customer service chatbots. This widespread integration raises important questions about how AI is reshaping human relationships, particularly in culturally rich societies such as Iran. Public attitudes toward AI remain mixed; a survey found that 52% of respondents felt more concerned than excited about AI developments (Faverio & Tyson, 2023), reflecting anxieties about the possible erosion of authentic interpersonal connection in an increasingly digital world. AI refers to the simulation of human intelligence by machines, including technologies such as machine learning, natural language processing, and robotics (Nass & Moon, 2000; Nass & Brave, 2005). While these systems enhance efficiency and accessibility, they also pose challenges for the depth and authenticity of human interaction (Sundar & Lee, 2022). As AI becomes more integrated into daily communication and social experiences, understanding its influence on relationships is particularly important in societies like Iran, where interpersonal bonds and traditional values play a central role in social life.

The digital age has also reshaped human identity, with individuals increasingly viewed as informational beings constantly connected to global networks (Dominguez, 2014). Although this connectivity facilitates communication, it can also reduce face-to-face interaction and weaken social skills (Russell, 2019). In Iranian society, where hospitality, family cohesion, and community engagement are deeply valued, this shift may contribute to declining empathy, reduced social cohesion, and the gradual erosion of cultural norms. Research shows that strong social connections are essential for mental and emotional well-being, while social isolation can produce negative health outcomes (Amichai-Hamburger & Ben-Artzi, 2003; Hohenstein et al., 2023). AI-driven platforms, however, may encourage behaviours such as social comparison and reduced emotional engagement (Duan et al., 2022). Studies on cultural change in the digital era (Acerbi, 2020) further suggest that technological immersion can reshape identity, learning, and social practices.

This article argues that although AI offers convenience and new forms of communication, it also challenges the authenticity and quality of relationships in Iranian society. As reliance on AI grows, there is a risk of increasingly superficial interaction (Dehnert & Mongeau, 2022), as well as the loss of emotional nuance that supports empathy and trust (Lee, 2020). Navigating this evolving landscape requires balancing technological advancement with the preservation of cultural values and meaningful human connection.

To examine the impact of artificial intelligence on interpersonal relationships and analyse the cultural and social challenges arising from it in Iran. This can be further broken down into sub-objectives that the project aims to address:

1. Identify the positive and negative effects of artificial intelligence on human relationships.
2. Identify cultural changes resulting from the spread of artificial intelligence in society.
3. Identify social challenges related to the penetration of artificial intelligence.
4. Provide local solutions for managing cultural and social challenges.

While this research investigates the nature of AI's impact on cultural and social dynamics in Iran, its relevance to the wider field of research remains. Contemporary literature identifies several converging themes that situate a country-specific study like this within broader debates: first, the emergence of human-AI intimacy and socio-affective alignment (Laestadius, et al., 2022; Maples, et al., 2024), where scholars worry that increasingly personalized agents reshape emotional bonds, trust, and care practices beyond conventional human relationships (Kirk, et al., 2025). Work in human-centred AI and HCI also stresses the need to move from technocentric evaluations toward context-sensitive studies (Raaijmakers, 2019; Belic, et al., 2019) that account for local meanings, practices, and user agency (Raees, et al., 2024), precisely the methodological gap this study addresses. An additional large and growing body of research on algorithmic and cultural bias also highlights how ostensibly neutral systems reproduce social inequalities and cultural misunderstandings unless evaluated in diverse settings (Celik, et al., 2022;

Feffer, et al., 2023). It is within these broader fields of research that this study situates itself, exploring a topic that remains under active investigation.

2. Methodology

This study employed a qualitative-dominant mixed-methods approach to investigate the cultural and social impacts of artificial intelligence (AI) on interpersonal relationships in Iran. The methodological design combined thematic analysis of semi-structured interviews with quantitative coding and frequency counts to ensure both depth and breadth in interpreting participants' perspectives. Mixed-methods approaches are particularly valuable in sociocultural research as they allow researchers to capture both subjective meaning-making processes and quantifiable patterns of responses, thereby increasing validity and explanatory power (Teddlie & Tashakkori, 2009; Creswell & Plano-Clark, 2018).

2.1. Data Collection

Data were collected through twelve semi-structured interviews using a purposive sampling method (Palinkas et al., 2013). This method was used to select the sample for the present study. was used to select the sample of the present study. In this method, the participants were selected and handpicked by the researcher because they either clearly have the phenomenon or characteristic of interest or are rich in information on a specific issue. In fact, this method is most often used when there is a need for expert samples (Palinkas, et al., 2013). In purposive sampling, it is not possible to determine in advance the number of participants required in the study in order to fully identify the phenomenon under study (Morgan, 1997). Interviews were conducted iteratively and continued until thematic saturation was reached, which refers to the point at which no new codes, concepts, or thematic insights emerged from additional data collection (Glaser & Strauss, 1967; Guest, et al., 2006). In this study, saturation was operationalised following the principles outlined by Guest, et al. (2006): (1) monitoring the emergence of new data within each interview; (2) comparing new data with previously identified categories; and (3) determining whether subsequent interviews contributed novel information relevant to the research questions.

To assess saturation systematically, after each interview, the researcher analyzed the collected data (i.e., opinions expressed by the participant) and examined whether new meaning units or categories appeared. Once several consecutive interviews produced no additional themes, sub-themes, or refinements, it was determined that thematic saturation had been achieved. This approach is consistent with Saunders, et al.'s (2018) conceptualisation of saturation as the point at which further data cease to add value to the conceptual development of the analysis.

2.2. Sampling

A sample refers to a subset of a population (Tailor, 2005), while 'sampling' is the technique used by researchers to select a manageable representation of that group (Sharma, 2017). The sample consisted of 12 participants, who were selected based on their experience, expertise in artificial intelligence, and willingness to participate. The list of sample participants is presented in Table 1. All interviews were recorded, transcribed verbatim, and anonymised to protect participants' identities, following established ethical practices for qualitative research (Wiles, 2013). This study utilised a combination of convenience, purposive, and snowball sampling methods (Cohen, et al., 2007) to gather participants. The researcher contacted colleagues at educational institutions who met the study's criteria, some of whom had a prior professional relationship with the researcher (Oppong, 2013). This convenience sampling method, though less rigorous than random sampling (Oppong, 2013), is frequently used in qualitative research (Dörnyei, 2007) and remains a valid approach for participant selection (Abedsaeidi & Amiraliakbari, 2015). Additionally, the researcher contacted colleagues who expressed an interest in the research area, forming a purposive sample (McChesney & Aldridge, 2019) to enhance the quality of data collected.

Table 1. List of Participants in the Qualitative Study

Rank	Field of Specialization	Gender	Interview Code
Associate Professor	Social Sciences Department	Man	M1
Assistant Professor	Social Sciences Department	Man	M2
Assistant Professor	Computer Engineering-Artificial Intelligence Orientation	Man	M3
Assistant Professor	Information Science and Knowledge Department	Man	M4

Rank	Field of Specialization	Gender	Interview Code
Assistant Professor	Computer Science	Woman	M5
PhD	Computer Engineering-Artificial Intelligence-Machine Learning	Man	M6
Masters	Computer Engineering, Artificial Intelligence and Robotics	Man	M7
Assistant Professor	Computer Engineering, Artificial Intelligence Orientation	Man	M8
PhD	Computer Engineering, Artificial Intelligence Orientation	Man	M9
PhD	Social Sciences Department	Man	M10
PhD	General Psychology Department	Man	M11
Associate Professor	Educational Technology Department	Man	M12

The use of convenience and purposive sampling, while practical for the study, introduces notable limitations regarding the representativeness and generalisability of the findings. Convenience and purposive sampling particularly constrain external validity: such samples can only be generalised to the subpopulation from which the sample is drawn and not to the entire population (Andrade, 2020). Estimates from convenience samples may also be biased, as participants are likely to differ systematically from the broader target population (Jager, et al., 2017). Consequently, the positive perceptions of AI's integration into Iranian society analyzed in this study may predominantly reflect the views of individuals who are more digitally engaged and already interested in AI ethics, potentially underrepresenting those who are less technologically proficient and/or more hesitant.

The selection of participants and the anonymisation of their data followed the Iranian National Ethical Guidelines for Research in the Humanities approved by the Ministry of Science, Research and Technology. Before each interview, the research purpose, participation requirements, and the right to withdraw at any stage were clearly explained verbally to all participants, including scholars from humanities and engineering fields. Explicit verbal consent for audio recording was obtained. In four cases where participants declined recording, interviews were documented through accurate handwritten notes. Because interviews were conducted in person and participants preferred an efficient process, verbal consent was used; however, all principles of informed consent, information, comprehension, voluntariness, and capacity were fully respected. Participant confidentiality

was ensured by removing all identifiable details, including names, affiliations, and positions, and replacing them with non-traceable codes. Raw data (audio files and written notes) were stored on an encrypted, password-protected device, with access restricted solely to the principal researcher who conducted the interviews.

The final sample included eleven men and one woman, creating a clear gender imbalance which warrants acknowledgement (Weber et al., 2021). This resulted from purposive, voluntary recruitment rather than intentional exclusion; such recruitment strategies can yield uneven response rates and remain acceptable when aligned with study aims and context (Patton, 2002; Sharp, 2003). However, the male-dominant sample may limit transferability, as gender can shape experiences and interpretations relevant to the topic, and the under-representation of women risks omitting gender-specific perspectives (Weber et al., 2021). Sample adequacy was assessed using qualitative standards of information power and thematic saturation, prioritizing analytic depth and recurring patterns over simple participant numbers (Guest et al., 2006; Malterud et al., 2016). To address limitations in reporting and interpretation, gender was treated as an explicit contextual factor in the analysis, and findings are presented cautiously with respect to transferability (Tracy, 2010). Future research should purposively recruit a more gender-balanced or stratified sample to examine potential gender differences more fully (Patton, 2002; Sharp, 2003).

2.3. Preparing an Interview

Semi-structured interviews are widely recognised for their flexibility in allowing participants to express perspectives in depth, while also providing a consistent structure for cross-comparison (Kvale & Brinkmann, 2015). The interview guide included open-ended questions aimed at four objectives: exploring the positive and negative effects of AI on interpersonal relationships, examining cultural changes resulting from AI's spread in Iranian society, identifying emerging social challenges, and eliciting locally appropriate solutions for managing these challenges.

Interview questions were developed based on the study's theoretical framework and research questions, following a semi-structured format (Kvale & Brinkmann, 2015) with an open-ended approach. The questions were designed to elicit information about factors indicating the impact of

artificial intelligence on interpersonal relationships and socio-cultural challenges.. The interview included questions such as:

1. Are you familiar with artificial intelligence technologies? If yes, which ones do you know or have you used?
2. How much do you deal with AI tools in your daily or professional life? Please give an example.

These questions were asked in general terms, and additional follow-up questions were posed as needed.

3. Analytical Framework

The analysis proceeded in two systematic stages. The first stage consisted of qualitative coding and thematic analysis. Each transcript was carefully read and manually coded according to the four research objectives, with emergent codes grouped into broader interpretive themes such as “reduced face-to-face interaction,” “cultural identity threats,” and “privacy concerns.” Thematic analysis was selected because it provides a rigorous yet flexible method for identifying, analyzing, and reporting patterns within qualitative data (Braun & Clarke, 2006). Representative quotations were extracted to preserve the nuance of participants’ voices and to capture contradictions or ambivalences in their accounts, aligning with best practices for thick description in qualitative research (Geertz, 1973). Additionally, responses were categorised as positive, negative, or neutral to highlight evaluative orientations toward AI.

3.1. Thematic Analysis

The first step in analyzing the data gathered in the semi-structured interviews was conducting a thematic analysis - a qualitative data analysis method that involves data collection, data familiarisation, coding and grouping of similar codes to derive themes (Braun & Clarke, 2019; McChesney & Aldridge, 2019) - which involved coding each response to determine if they correlated to the four pre-determined objectives (Krippendorff, 2019) of this article: (1) the positive and negative effects of AI on interpersonal relationships, (2) cultural changes arising from AI adoption, (3) emerging social challenges, and (4) locally appropriate solutions. Following a deductive reasoning paradigm (Braun & Clarke, 2019) this article

conducted thematic analysis within the confines of predetermined hypotheses (Attride-Stirling, 2001; Tuckett, 2005). If responses correlated with one (or more) of the four pre-determined objectives, they were coded and recorded under each category. Figure 1 illustrates the thematic analysis of the M1 interview responses.

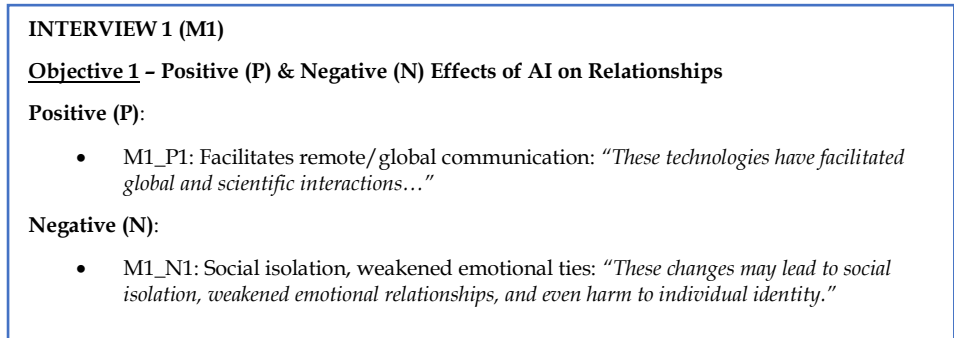


Figure 1. coding and thematic analysis of M1 interview transcript

The analysis of the study's data were informed by the researcher's own social position (Harkness et al., 2010; Kvale, 2007), which prompted ongoing self-reflexivity throughout the interpretive process. This involved critically considering how personal experiences and circumstances shaped the interpretation of the data (Alvesson & Sköldberg, 2018; Merriam & Grenier, 2019). Within an interpretivist framework, such reflexivity is essential, as it acknowledges that the construction of knowledge is inevitably influenced by the researcher's assumptions and perspectives (Alvesson & Sköldberg, 2018). Engaging in this reflective practice enabled the researcher to recognise the inherently subjective aspects of the work and the ways in which their own background and biases informed the research (Lincoln et al., 2011). This approach is especially valuable in small-N qualitative studies, where it supports systematic analysis while remaining attentive to contextual nuance (Yin, 2018).

After conducting the semi-structured interviews with each participant, their interview transcripts underwent thorough examination using NVivo 15 software, with the researcher identifying and documenting phrases from

them. These phrases were selected by the researcher, who is a formally trained educator, with a predisposition to analyse written work. Phrases were selected if they met one (or more) of the following criteria:

- *Significance and impact.* Phrases that reflect the deductive framework of the study and correlate with the four pre-determined objectives the researchers set out to investigate.
- *Clarity and conciseness.* Phrases that articulate complex ideas in a clear and concise manner, making them easier to understand and communicate.
- *Repetition of concepts.* Phrases that appear frequently within interview transcripts may indicate not only the emphasis placed on them by participants but also a consensus in the field, thus warranting particular attention.

Using this theoretical framework of data collection, the data were then organized into a thematic table (Table 2) that categorises responses according to four overarching objectives: 1) Positive and Negative Effects of AI on Relationships, 2) Cultural Changes in Iran, 3) Social Challenges, and 4) Local Solutions. Within each objective, sub-themes were identified by coding recurring concepts and statements across interviews, allowing for a comparison of similarities, differences, and unique insights among participants. Each sub-theme is illustrated with representative codes drawn from individual interviews, highlighting the frequency and context of key ideas. This approach enables a clear visualisation of trends, cross-cutting patterns, and areas of divergence, providing a structured framework for understanding the multifaceted impacts of AI on Iranian society.

Table 2. Cross-Interview Thematic Analysis

Theme	Sub-theme	Human (Principal) Coder: Identified words or phrases	AI (Secondary) Inter-coder Identified words or phrases
Positive Effects of AI on Relationships	Facilitates Communication	7	6
	Supports Professional & Academic Work	6	6
	Daily Convenience & Efficiency	6	5
	Emotional / Social Assistance	5	4
	Cultural Adaptation & Alignment	2	3

Theme	Sub-theme	Human (Principal) Coder: Identified words or phrases	AI (Secondary) Inter-coder Identified words or phrases
Negative Effects of AI on Relationships	Reduced Face-to-Face Interactions	7	6
	Weakened Emotional/Family Bonds	10	9
	Dependency on Technology / Overreliance	7	8
	Misinformation / Trust Issues	4	4
	Isolation / Loneliness	4	4
	Reduced Human Skills	4	4
Cultural Changes in Iran	Shift to Digital / Virtual Lifestyles	5	5
	Youth as Early Adopters	5	4
	Cultural Identity Threatened	4	5
	Values and Social Norm Shifts	6	5
	Limited Cultural Penetration (Emerging)	3	4
Social Challenges	Inequalities / Digital Divide	8	6
	Dependency / Overreliance	7	6
	Privacy & Data Security	4	4
	Mental Health / Isolation	5	4
	Cultural & Social Norm Erosion	2	3
Local Solutions	Education & Awareness	11	9
	Cultural Adaptation / Local Content	9	7
	Policy, Regulation, & Ethics	9	8
	Infrastructure & Access Equality	5	4
	Self-Regulation / Responsible Use	4	4

3.2. AI as an Inter-coder and Krippendorff’s Alpha

To enhance the reliability and validity of the thematic analysis, this study employed a generative AI large language model (LLM) as an alternative secondary inter-coder to review the coding of interview transcripts. Following initial coding by the principal researcher, the LLM independently analyzed anonymised transcripts to identify recurring themes and sub-themes, providing a comparative check against human-generated codes. This approach draws on emerging literature demonstrating the utility of AI-assisted qualitative analysis for augmenting inter-coder reliability (Wei et al., 2022), particularly in small-N studies where resource constraints limit multiple human coders (Liang, et al., 2022; Chew, et al., 2023). By cross-

referencing AI-generated codes with those of the researcher, discrepancies were identified, discussed, and resolved through iterative refinement (Roberts, 2020), akin to traditional double-coding practices (MacQueen, et al., 1998; O'Connor & Joffe, 2020). The AI-assisted process increased confidence in the consistency and validity of thematic categorisations while preserving the interpretive nuance central to both inductive and deductive qualitative approaches (Saldaña, 2021; Ziang, et al., 2023).

To evaluate consistency between a human coder and an AI-assisted intercoder, we conducted a systematic intercoder reliability analysis using Krippendorff's Alpha (2011; 2019). This method was selected because the coding scheme involved ordered categories representing the intensity or magnitude of identified evidence within each sub-theme (Hayes & Krippendorff, 2007). The dataset comprised 27 sub-themes across five major thematic domains related to AI integration in Iran (e.g., positive effects on relationships, negative effects, cultural change, social challenges, and local solutions). For each sub-theme, both the human coder and the AI intercoder recorded the number of words or phrases supporting its presence in interview data. Since Krippendorff's Alpha (2011;2019) requires categorical rather than raw count data, we transformed frequency counts into ordinal categories reflecting low, medium, and high evidence levels: Low (1): 0-3 identified phrases, Medium (2): 4-7 identified phrases, and High (3): 8-11 identified phrases. This transformation enabled use of an ordinal distance metric appropriate for Krippendorff's Alpha (2011;2019).

Each of the 27 sub-themes was assigned two ordinal values, one from the human coder and one from the AI intercoder, resulting in 27 paired observations. These pairs formed the basis for computing observed and expected disagreement. Following Krippendorff's approach (2011;2019) for ordinal data, we defined a **distance function** based on squared normalised differences:

$$\delta_{ij} = \left(\frac{|i - j|}{\text{max difference}} \right)^2$$

For a 3-point ordinal scale (1-3), the maximum possible difference is 2, giving:

- Agreement (difference = 0): $\delta = 0$
- 1-step distance (difference = 1): $\delta = 0.25$
- 2-step distance (difference = 2): $\delta = 1$

This weighting ensures that more severe coder disagreements contribute proportionally greater error, which in turn would provide an indication as to the validity of the human / AI / principal coder's findings.

3.2.1. Observed Disagreement (D_o)

Observed disagreement was calculated by summing the distance values for all human-AI coding differences across sub-themes and dividing by the total number of items. In the dataset, 22 cases showed perfect agreement, 5 cases showed a 1-point difference, and 0 cases showed a 2-point difference. Using the ordinal distance weights:

$$D_o = \frac{(5 \times 0.25)}{27} = 0.0463$$

This reflects very low observed disagreement between coders.

3.2.2. Expected Disagreement (D_e)

Expected disagreement represents the amount of disagreement that would occur by chance, based on how often each category was used across both coders. We combined all human and AI ratings (54 total observations) to compute category densities:

- Category 1: 5 occurrences
- Category 2: 37 occurrences
- Category 3: 12 occurrences

Proportions:

- $p_1 = 0.0926$
- $p_2 = 0.6852$
- $p_3 = 0.2222$

Expected disagreement is calculated using:

$$D_e = \sum_{i \neq j} p_i p_j \delta_{ij}$$

Accounting for both symmetrical pairs, the final expected disagreement was $D_e = 0.14905$.

3.2.3. Calculation of Krippendorff's Alpha

Krippendorff's Alpha (2011;2019) for ordinal data is computed as:

$$\alpha = 1 - \frac{Do}{De} \quad \alpha = 1 - \frac{0.0463}{0.14905} = 0.6895$$

Krippendorff's Alpha (2011;2019) for the dataset was **0.69**, which falls within the range generally interpreted as indicating moderate to substantial agreement (0.61–0.80). This result suggests that the principal human coder and the AI secondary intercoder showed a high level of consistency in their coding decisions once the frequency counts were converted into an ordinal scale, with only minor variations in the degree to which each sub-theme was coded was coded.

4. Findings

The analysis of twelve interviews indicates that AI is perceived as a transformative yet double-edged force in Iranian society, producing both notable benefits and challenges. Positive effects were reported by all participants, with facilitating communication the most common theme, coded in 7 of 12 interviews (58%), often in global, remote, or educational contexts. AI's support for professional and academic work appeared in 6 interviews (50 %), while daily convenience and efficiency were noted in 5 (42 %). Emotional or social assistance and culturally adaptive features were mentioned less frequently, in 5 interviews (42 %) and 2 interviews (17 %), respectively.

Conversely, negative effects were widespread: reduced face-to-face interaction appeared in 7 interviews (58%) and weakened emotional or family bonds in 7 (58%). Dependency on technology emerged in 7 interviews (58%), while concerns about misinformation or trust issues appeared in 4 (33%), and isolation or loneliness in 4 (33%). An additional 4 interviews (33%) highlighted reduced human skills such as empathy or critical thinking. In terms of cultural change, youth-driven adoption was coded in 5 interviews (42%), alongside shifts to digital lifestyles in 5 (42%). Perceived threats to cultural identity were raised in 4 interviews (33%), values or social norm shifts in 5 (42%), and limited cultural penetration in 3 (25%).

Social-level challenges were also evident: inequalities and the digital divide were cited in 8 interviews (67%), societal overreliance in 7 (58%), and privacy or data security concerns in 4 (33%). Mental health impacts such as isolation surfaced in 4 interviews (33%), and cultural or social norm erosion in 2 (17%). To mitigate these effects, participants proposed local solutions, with education and awareness programs mentioned in 9 interviews (75%), cultural adaptation and locally aligned AI content in 7 (58%), and policy, regulation, and ethics frameworks in 6 (50%). Infrastructure and access equality were raised in 5 interviews (42%), and responsible individual use in 4 (33%). Overall, while AI offers clear opportunities for connectivity and productivity, its broader social and cultural impacts require proactive, multi-level responses combining education, policy, and cultural adaptation.

The interview findings reveal a complex and ambivalent perception of artificial intelligence in Iranian society. When placed alongside existing Iran-focused scholarship, a coherent narrative emerges: AI is broadly viewed as an enabler of communication, education, and productivity, while simultaneously intensifying structural, cultural, and relational pressures. This duality reflects longstanding patterns in Iranian digital-society research, where technology adoption unfolds within uneven access, cultural negotiation, and state-society tensions. Across all twelve interviews, participants highlighted significant benefits. The most frequently noted was enhanced communication (58%), which aligns with Rahimi's (2015) argument that digital technologies often function as mediating tools allowing Iranians to bypass geographic and infrastructural constraints. For young people and globally dispersed families, AI-supported translation, content generation, and messaging expand communicative capacities beyond local linguistic or political boundaries. These uses echo Rajabi and Nasrollahi's (2023) findings on how AI-driven platforms facilitate more fluid cultural participation and self-expression, continuing earlier trends in Iranian digital media adoption.

Professional and academic assistance (50%) was another major theme. Participants described AI as improving productivity through drafting, research support, and information analysis, mirroring insights from Mahboudi, et al. (2017) on computers' role in widening educational opportunities. Their experiences also reflect Mahmoudi, et al.'s (2025) findings that AI enhances efficiency and innovation in Iranian knowledge-

based organisations. These benefits are especially meaningful in a context where access to global academic networks and current resources remains constrained. Participants also cited convenience and efficiency (42%), and emotional or social assistance (42%) and these benefits align with Atwood's (2025) argument that AI in Iran is framed as both a modernising force and a practical tool for coping with systemic limitations. In a society marked by economic pressure and heavy daily workloads, AI often functions as a mechanism for reducing cognitive and emotional burden.

Yet participants expressed an equally strong set of concerns. Reduced face-to-face interaction (58%) and weakened emotional or family bonds (58%) mirror cultural anxieties identified by Rajabi and Nasrollahi (2023), who show that AI-based platforms are often perceived as eroding communal norms and traditional interpersonal dynamics. Iran's strong family-oriented culture heightens fears of relational fragmentation, reinforcing broader societal narratives that present technology as both indispensable and culturally disruptive. Dependency on technology (58%) emerged as another central concern, with participants describing discomfort with how reliant they had become on AI, a sentiment resonant with Atwood's (2025) characterisation of a national "double bind": AI is embraced for its modernising potential but feared for its implications for autonomy and control. Individual dependency thus mirrors anxieties about systemic dependency on technologies developed outside Iran. Such concerns resonate with broader analyses of AI as a site of geopolitical contestation, where public discourse reflects tensions over technological sovereignty, global power asymmetries, and digital dependency (Salehi et al., 2025).

Concerns about misinformation, trust, and loss of human skills (each reported in 33% of interviews) map onto broader structural challenges. As Qadikolaei, et al. (2022) show, Iran's digital divide, marked by uneven access and variable digital literacy, limits many citizens' ability to critically evaluate online content. Participants' fear of diminished critical thinking or empathy thus reflects uneven digital skill development and inconsistent exposure to reliable information ecosystems. Cultural change was another major cluster. Youth-driven adoption (42%) and shifts toward digital lifestyles (42%) parallel the generational patterns identified by Rajabi and Nasrollahi (2023), wherein Iranian youth treat digital spaces as extensions of identity formation

and cultural engagement. Concerns about eroding cultural identity (33%) and shifting values (42%) correspond to Atwood's (2025) analysis of national narratives that depict AI as both necessary for modernisation and a potential threat to cultural autonomy. Three participants (25%) emphasised that AI tools often fail to reflect local cultural specificities, revealing tensions between globalised technologies and Iran's socio-cultural landscape.

Social-level concerns further emphasised inequality and unequal access to AI tools and digital resources (67%), which directly mirror Qadikolaei et al.'s (2022) findings on provincial disparities in digital access. Participants' accounts underscore how digital inequality shapes all other dimensions of AI usage and perception. Other issues including societal dependency (58%), privacy and security (33%), and erosion of social norms (17%), reinforce Rahimi's (2015) warning that rapid technological adoption without tailored regulation can produce cultural strain and intensify public anxiety. These fears about data control also align with Atwood's (2025) observation that Iranian public discourse often frames AI within geopolitical and surveillance concerns.

Overall, the findings depict AI in Iran as simultaneously empowering and disruptive. It expands communication, productivity, and opportunity, yet challenges cultural norms, widens inequalities, and raises concerns about dependency. When situated within Iranian scholarship, these perceptions reveal an ongoing negotiation between modernity, identity, and technological change. Similar patterns have been observed in digital public discourse, where emotional and rhetorical responses to AI-driven disruption function not merely as individual reactions but as mechanisms for constructing collective identity, negotiating institutional trust, and shaping shared imaginaries about technology's social role (Sabbar & Habib Zadeh Khiyaban, 2023). The evidence highlights the need for coordinated interventions in education, policy, and cultural localization to help ensure that AI supports social cohesion, cultural continuity, and equitable development.

5. Discussion

As these findings demonstrate, artificial intelligence (AI) has increasingly permeated daily life, transforming how individuals communicate, form relationships, and interact socially. The rapid evolution of AI technologies

has reshaped human practices, influencing both personal and communal dynamics. From digital communication to emotional companionship, AI's influence extends across multiple layers of social interaction, presenting both opportunities and challenges.

5.1. AI in Communication

Social media platforms rely heavily on AI algorithms to curate content, shape engagement, and personalize user feeds by analyzing interactions such as likes, shares, and time spent on posts (Banas et al., 2022). This personalisation optimises user engagement but also fosters echo chambers, limiting exposure to diverse viewpoints and reinforcing pre-existing beliefs (Duan et al., 2022). Such environments may contribute to the polarization of communities, affecting not only online discourse but also real-world social cohesion. Users increasingly interact with algorithmically curated content rather than engaging in substantive dialogue, raising concerns about the depth and authenticity of digital interactions.

AI-powered chatbots and virtual assistants have transformed professional and personal communication. In customer service, chatbots efficiently handle inquiries, provide immediate information, and resolve issues around the clock, reducing operational costs by up to 30% (Endacott & Leonardi, 2022; IBM, 2024). On a personal level, virtual assistants such as Siri, Alexa, and Google Assistant facilitate everyday tasks, enabling intuitive, natural-language interactions (Sundar, 2020). These advancements improve convenience and accessibility; however, they may also reduce human-to-human communication, potentially contributing to social isolation and dependence on technology (Brandtzaeg et al., 2022; Darioshi & Lahav, 2021).

5.2. AI in Relationships

AI has significantly altered romantic and emotional relationships. Dating applications such as Tinder and Bumble employ algorithms to analyse preferences, behaviours, and demographics, enhancing match predictions and streamlining partner selection (Laapotti & Raappana, 2022). While these tools increase opportunities for connection, they may also encourage superficial interactions and "choice overload," where an abundance of options results in decision fatigue and diminished satisfaction (Hancock et al., 2020).

Beyond dating, AI companions such as Replika and AI Dungeon provide emotional support and virtual companionship, particularly benefiting individuals who experience loneliness or social anxiety (Sundar & Chen, 2023). These AI-driven characters adapt to users' emotional cues, offering personalized engagement. While such companions can provide comfort and reduce perceived isolation, ethical questions arise regarding the authenticity of these relationships and the long-term impact on social skills (Hohenstein et al., 2023; Dehnert & Mongeau, 2022). Increasing reliance on AI for emotional support may inadvertently diminish real-life social competence, creating a paradox where individuals feel less lonely while simultaneously experiencing isolation from human interaction.

5.3. Decreased Face-to-Face Interactions

The rise of AI-mediated communication has coincided with a decline in face-to-face engagement. A survey by LivePerson (2021) reported that 65% of global participants reported communicating more digitally than in person; this figure rises to 74% in English-speaking countries. Younger generations, accustomed to texting and social media, often prefer these digital channels to traditional communication methods. While convenient, digital interaction may reduce social skills such as active listening, interpreting nonverbal cues, and engaging in spontaneous dialogue (Zhang et al., 2024).

Instant communication fosters expectations of immediate responses, sometimes generating pressure, misinterpretation, and conflict (Matlabinejad et al., 2023). However, in educational settings, AI can enhance communication. For example, AI-powered chatbots improve interaction quality in online learning, increasing comfort levels among students communicating with unfamiliar peers (Mostafa et al., 2024). AI instructor self-disclosure has been shown to foster emotional bonding, engagement, and positive learning experiences, highlighting the potential of AI to support interpersonal communication while maintaining pedagogical effectiveness (Tai, 2020; Zhang et al., 2024).

5.4. The Psychological Impact of AI on Relationships

Despite advances in natural language processing and machine learning, AI remains limited in interpreting human emotions. Unlike humans, who rely on subtle cues such as tone, facial expressions, and body language, AI

primarily depends on algorithms and data, often misreading or overlooking emotional states (Sundar & Chen, 2023; Nass & Moon, 2000). For instance, customer service chatbots may respond efficiently but fail to convey empathy, potentially exacerbating frustration (Banas et al., 2022).

Social media and digital communication also promote an illusion of connection. Online personas are often curated, presenting idealised versions of users that may not reflect reality (Guzman & Lewis, 2020; Duan et al., 2022). Interactions are frequently brief and superficial; accumulating friends or followers does not necessarily equate to meaningful engagement, which can negatively impact emotional health (Brandtzaeg et al., 2022; Hohenstein et al., 2023). Younger generations, in particular, may prioritise digital interactions over in-person connections, increasing susceptibility to anxiety and depression.

The paradox of feeling connected yet lonely is heightened by AI reliance for companionship, creating a cycle where individuals substitute machine interaction for authentic human engagement (Gunkel, 2012; Mijwil et al., 2022). During the COVID-19 pandemic, digital tools mitigated isolation but could not fully replicate the emotional richness of physical presence, potentially fostering a long-term preference for virtual communication (Tai, 2020).

5.5. The Impact on Family and Friend Dynamics

AI has reshaped family communication through digital platforms, enabling real-time coordination and interaction across distances (Gong et al., 2021). AI-driven features such as smart notifications and automated responses enhance efficiency but may also introduce misunderstandings due to the absence of tone, body language, and synchronous dialogue (Brito & Dias, 2020; Carvalho et al., 2015). Friendship dynamics have similarly evolved. AI and social media allow connections based on shared interests rather than physical proximity, expanding opportunities for social engagement (Druga et al., 2022; Garg et al., 2022). Algorithms may suggest potential friends, facilitating community formation, but online convenience can lead to superficiality, emphasising quantity over quality (Higgins, 2019). AI-mediated conflict resolution tools provide guidance but often lack the emotional intelligence necessary for genuine reconciliation (Lee & Yoon, 2021; De Tongi et al., 2021). Generational differences significantly influence AI adoption. Digital natives embrace AI features as integral to their social interactions, while older adults

may feel alienated or overwhelmed by technological changes, creating intergenerational disconnects (Liao et al., 2023; Hata et al., 2019; Galaz et al., 2021). Addressing these divides requires patience, empathy, and efforts to bridge traditional and digital communication modes.

5.6. The Ethical Implications of AI in Relationships

AI integration raises ethical concerns, particularly regarding privacy, consent, and dependency. Platforms collect extensive user data, including interactions, preferences, and emotional cues, often without explicit consent (Crawford, 2021; Bie, 2023). Dating apps exemplify this, tracking behaviours to enhance matchmaking while potentially breaching trust or exploiting sensitive information (Gan & Wang, 2024; Greene, 2020). Dependency on AI for emotional support presents further challenges. While AI provides immediate comfort, it lacks genuine empathy, potentially reducing individuals' engagement in authentic relationships (Wu, 2024; Marcos-Pablos & García-Peñalvo, 2022; Chen & Tang, 2024). Over-reliance may isolate individuals and encourage a preference for AI companionship, raising questions about the social consequences of substituting human interaction with artificial ones (Morgante et al., 2024; Epley et al., 2007; Petina et al., 2023).

5.7. Reclaiming Authenticity in Relationships

Maintaining authenticity in relationships requires balancing technology use with human connection, fostering emotional intelligence, and prioritizing meaningful engagement (Sundar & Lee, 2022; Hancock et al., 2020; McStay, 2018; Marcos-Pablos & García-Peñalvo, 2022; Atwood, 2025). Setting boundaries around AI and digital platforms, promoting face-to-face communication, and thoughtfully integrating technology can enhance rather than replace genuine interaction (Lee, 2020; Carvalho et al., 2015; Brandtzaeg et al., 2022; De Togni et al., 2021).

Establishing tech-free spaces, such as family meals or social gatherings, supports uninterrupted engagement and preserves nonverbal communication cues (Greene, 2020; Bie & Zeng, 2024; Deneke et al., 2021). Regular in-person interactions sustain empathy, active listening, and trust – essential for resolving conflict and building genuine bonds (McStay, 2020; Morgante et al., 2024; Epley et al., 2007). Community-based programmes and workshops on emotional skills, conflict resolution, and communication can

strengthen social cohesion and encourage authentic engagement (Marvin, 2006; Cha et al., 2022). Participation in social clubs, volunteer work, and group activities fosters belonging, mitigates digital isolation, and provides opportunities for face-to-face connection (Pentina et al., 2023; Hennig-Thurau et al., 2022; Wu, 2024). While reclaiming authenticity remains challenging due to miscommunication and evolving norms, open dialogue, adaptability, and intentional engagement are crucial to sustaining meaningful human relationships in an AI-driven society (Gremsl & Hödl, 2022; Marvin, 2006).

6. Conclusion

As artificial intelligence becomes increasingly embedded in everyday life, its influence on interpersonal relationships in Iranian society presents both opportunities and challenges. AI-driven technologies, such as social media algorithms, messaging platforms, and virtual assistants, have made communication faster and more accessible, allowing families and friends to stay connected across long distances. In a society where strong family ties, hospitality, and community cohesion are deeply valued, these tools can help sustain relationships despite migration, busy schedules, or geographic separation. However, the convenience of digital interaction also risks reducing the frequency and quality of face-to-face encounters that traditionally nurture emotional closeness and trust. The growing reliance on AI-mediated communication may subtly reshape how individuals express empathy, resolve conflict, and build intimacy. Interacting primarily through screens and algorithms can limit exposure to the emotional nuance, body language, and shared experiences that deepen relationships. For younger generations in particular, the ease of AI-driven interaction may encourage a shift away from long-standing social customs, potentially weakening traditions rooted in personal presence and communal engagement. There is also a risk that algorithmic curation of content and social networks will create echo chambers, narrowing perspectives and contributing to social polarization within communities.

Psychologically, AI offers both support and concern. Chatbots and digital companions can provide a sense of connection or assistance, yet they cannot fully replicate the emotional richness of human relationships. This may foster what researchers call an “illusion of connection,” where individuals feel

socially engaged online while experiencing loneliness or isolation offline. In a culture that places high importance on collective belonging and interpersonal warmth, such a disconnect could have meaningful implications for well-being. To navigate this evolving landscape, a balanced approach is essential. Promoting digital literacy, emotional awareness, and critical engagement with AI can help individuals use technology thoughtfully rather than dependently. Encouraging community spaces, family gatherings, and in-person interaction can preserve the relational depth central to Iranian culture. Ultimately, AI may be most beneficial when embraced as a supportive tool that enhances communication and connection without replacing the human bonds that sustain social life and cultural continuity.

Conflict of Interest

The author declares no conflict of interest.

Funding

No funding agency or institution influenced the research design, analysis, or interpretation of results.

References

- Abedsaeidi J., & Amiraliakbari S. (2015). *Research Method in Medical Sciences and Health*. Salemi
- Acerbi, A. (2020) *Cultural Evolution in a Digital Age*. Oxford University Press.
- Afifi, T. D., Zamanzadeh, N., Harrison, K., & Callejas, M. A. (2018). WIRED: The impact of media and technology use on stress (cortisol) and inflammation (interleukin IL-6) in fast-paced families. *Computers in Human Behavior*, 81, 265–273. <https://doi.org/10.1016/j.chb.2017.12.010>
- AIPRM. (2024). *AI Statistics 2024*. <https://www.aiprm.com/en-gb/ai-statistics/>
- Amichai-Hamburger, Y., & Ben-Artzi, E. (2003). Loneliness and Internet use. *Computers in Human Behaviour*, 19(1), 71–80. [https://doi.org/10.1016/S0747-5632\(02\)00014-6](https://doi.org/10.1016/S0747-5632(02)00014-6)
- Andrade, C. (2020). The Inconvenient Truth About Convenience and Purposive Samples. *Indian Journal of Psychological Medicine*, 43(1), 86–88.
- Attride-Stirling, J. (2001). Thematic networks: An analytical tool for qualitative research. *Qualitative Research*, 1(3), 385–405
- Atwood, B. (2025). Artificial Intelligence in Iran: National Narratives and Material Realities. *Iranian Studies*, 1–18. <https://doi.org/10.1017/irn.2024.63>
- Banas, J., Palomares, N., Richards, A., Keating, D., Joyce, N., & Rains, S. (2022). When machine and bandwagon heuristics compete: Understanding users' response to conflicting AI and crowdsourced fact-checking. *Human Communication Research*, 48(3), 430–461. <https://doi.org/10.1093/hcr/hqac010>
- Belic, M., Bobic, V., Badza, M., Solaja, N., Djuric-Jovicic, M., & Kostic, V. (2019). Artificial intelligence for assisting diagnostics and assessment of parkinson's disease - a review. *Clinical Neurology and Neurosurgery*, 184, 105442. <https://doi.org/10.1016/j.clineuro.2019.105442>
- Bie, J. H. (2023). Platformized digital interactions: Affective practices based on the availability of technology. *Young Journal*, 4, 22–25. <https://doi.org/10.15997/j.cnki.qnjz.2023.04.007>
- Bie, J. H., & Zeng, Y. T. (2024). Algorithmic imagination of platform participation and affective networks: An analysis of users on Xiaohongshu. *China Youth Research*, 2, 15–23. <https://doi.org/10.19633/j.cnki.11-2579/d.2024.0018>
- Brandtzaeg, P., Skjuve, M., & Følstad, A. (2022). My AI friend: How users of a social chatbot understand their human–AI friendship. *Human Communication Research*, 48(3), 404–429. <https://doi.org/10.1093/hcr/hqac008>
- Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, 3(2), (2006). 77–101. <https://doi.org/10.1191/1478088706qp063oa>
- Braun, V., & Clarke, V. (2019). Reflecting on reflexive thematic analysis." *Qualitative Research in Sport, Exercise and Health*, 11(4), 589–597.

- Brito, R., & Dias, P. (2020). Which apps are good for my children? How the parents of young children select apps. *International Journal of Child-Computer Interaction*, 26, 100188. <https://doi.org/10.1016/j.ijcci.2020.100188>
- Carvalho, J., Francisco, R., & Relvas, A. P. (2015). Family functioning and information and communication technologies: How do they relate? A literature review. *Computers in Human Behavior*, 45, 99–108. <https://doi.org/10.1016/j.chb.2014.11.037>
- Celik, I., Dindar, M., Muukkonen, H., & Järvelä, S. (2022). The promises and challenges of artificial intelligence for teachers: A systematic review of research. *TechTrends*, 66(4), 616–630.
- Cha, D. L., Jiang, Z. H., & Cao, G. H. (2022). A study of user-perceived algorithmic anxiety and its structural dimensions in information systems. *Intelligent Science*, 6, 66–73. <https://doi.org/10.13833/j.issn.1007-7634.2022.06.009>
- Chen, S. H., & Tang, L. (2014). Human-machine love: Emotional interchain and emotional intelligence coupling of artificial intelligence partners. *Journal of Hainan University*, 9, 1–9. <https://doi.org/10.15886/j.cnki.hnus.202405.0437>
- Chew, R., Bollenbacher, J., Wenger, M., Speer, J., & Kim, A. (2023). LLM-Assisted Content Analysis: Using Large Language Models to Support Deductive Coding. *ArXiv*, <https://doi.org/10.48550/arXiv.2306.14924>
- Cohen, L., Manion, L., & Morrison, K. (2007). *Research Methods in Education*. Routledge
- Crawford, K. (2021). Time to regulate AI that interprets human emotions." *Nature*, 592, 7853. <https://doi.org/10.1038/d41586-021-00868-5>
- Creswell, J., & Plano Clark, V. (2018). *Designing and conducting mixed methods research* (3rd ed.). SAGE Publications.
- Darioshi, R., & Lahav, E. (2021). The impact of technology on the human decision-making process. *Human Behavior and Emerging Technologies*. 3(2), 1-10. <http://dx.doi.org/10.1002/hbe2.257>
- De Togni, G., Erikainen, S., Chan, S., & Cunningham-Burley, S. (2021). What makes AI 'intelligent' and 'caring'? Exploring affect and relationality across three sites of intelligence and care. *Social Science and Medicine*, 277, 113874. <https://doi.org/10.1016/j.socscimed.2021.113874>
- Dehnert, M., & Mongeau, P. A. (2022). Persuasion in the age of artificial intelligence (AI): Theories and complications of AI-based persuasion. *Human Communication Research*, 48(3), 386–403. <https://doi.org/10.1093/hcr/hqac006>
- Denzin, N. (2017). *The research act: A theoretical introduction to sociological methods* (4th ed.). Routledge.
- Domínguez, M. (2014). Einstein versus neutrinos: The two cultures revisited with the media coverage of a scientific news item in cartoons. *Science Communication* 36(2), 248–25.
- Dörnyei, Z. (2007). *Research methods in applied linguistics*. Oxford University Press

- Druga, S., Christoph, F. L., & Ko, A. J. (2022). Family as a third space for AI literacies: How do children and parents learn about AI together? In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*. 1-17.
- Duan, Z., Li, J., Lukito, J., Yang, K., Chen, F., Shah, D., & Yang, S. (2022). Algorithmic agents in the hybrid media system: Social bots, selective amplification, and partisan news about COVID-19." *Human Communication Research*, 48(3), 516-542. <https://doi.org/10.1093/hcr/hqac012>
- Endacott, C., & Leonardi, P. (2022). Artificial intelligence and impression management: Consequences of autonomous conversational agents communicating on one's behalf. *Human Communication Research*, 48(3), 462-490. <https://doi.org/10.1093/hcr/hqac009>
- Epley, N., Waytz, A., & Cacioppo, J. T. (2007). On seeing human: A three-factor theory of anthropomorphism. *Psychological Review*, 114(4), 864-886. <https://doi.org/10.1037/0033-295X.114.4.864>
- Faverio, M., & Tyson, A. (2023). What the data says about Americans' view of artificial intelligence. *Pew Research Centre*. <https://www.pewresearch.org/short-reads/2023/11/21/what-the-data-says-about-americans-views-of-artificial-intelligence/>
- Feffer, M., Martelaro, N., & Heidari, H. (2023). The AI incident database as an educational tool to raise awareness of AI harms: A classroom exploration of efficiency, limitations & future improvements. *arXiv*. <https://arxiv.org/abs/2310.06269>
- Galaz, V., Centeno, M. A., Callahan, P. W., Causevic, A., Patterson, T., Brass, I., et al. (2021). Artificial intelligence, systemic risks, and sustainability. *Technology in Society*, 67, 101741. <https://doi.org/10.1016/j.techsoc.2021.101741>
- Gan, L. H., & Wang, H. (2024). From emotional projection to digital emotion: Emotional transformation of human-computer interaction in digital landscapes." *Modern Publishing*, 3, 27-38.
- Garg, R., Cui, H., Seligson, S., Zhang, B., Porcheron, M., Clark, L., et al. (2022). The last decade of HCI research on children and voice-based conversational agents. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*. 1-19.
- Geertz, C. (1973). *The interpretation of cultures*. Basic Books.
- Glaser, B. & Strauss, A. (2017). *Discovery of Grounded Theory: Strategies for Qualitative Research*. Routledge.
- Gong, W. J., Wong, B. Y. M., Ho, S. Y., Lai, A. Y. K., Zhao, S. Z., Wang, M. P., et al. (2021). Family e-chat group use was associated with family well-being and personal happiness in Hong Kong adults amidst the COVID-19 pandemic. *International Journal of Environmental Research and Public Health*, 18, 9139. <https://doi.org/10.3390/ijerph18179139>
- Gossett, S. (2023). Emotion AI: 3 experts on the possibilities and risks. <https://builtin.com/artificial-intelligence/emotion-ai>

- Greene, G. (2020). The ethics of AI and emotional intelligence. <https://partnershiponai.org/paper/the-ethics-of-ai-and-emotional-intelligence/>
- Gremsl, T., & Hödl, E. (2022). Emotional AI: Legal and ethical challenges. *Information Policy*, 27, 163–174. <https://doi.org/10.3233/IP-211529>
- Guest, G., Bunce, A., & Johnson, L. (2006). How Many Interviews Are Enough? An Experiment with Data Saturation and Variability. *Field Methods*, 18(1), 59-82. <https://doi.org/10.1177/1525822X05279903>
- Gunkel, D. (2012). Communication and artificial intelligence: Opportunities and challenges for the 21st century." *Communication +1*, 1(1), 1-23. <https://doi.org/10.7275/R5QJ7F7R>
- Guzman, A., & Lewis, S. (2020). Artificial intelligence and communication: A human-machine communication research agenda. *New Media and Society*, 22(1), 70–86. <https://doi.org/10.1177/1461444819858691>
- Hancock, J., Naaman, M., & Levy, K. (2020). AI-mediated communication: Definition, research agenda, and ethical considerations." *Journal of Computer-Mediated Communication*, 25(1), 89–100. <https://doi.org/10.1093/jcmc/zmz022>
- Hata, A., Inam, R., Raizer, K., Wang, S., & Cao, E. (2019). AI-based safety analysis for collaborative mobile robots." In *2019 24th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA)*, 1722–1729.
- Hayes, A., & Krippendorff, K. (2007). Answering the Call for a Standard Reliability Measure for Coding Data. *Communication Methods and Measures*, 1(1), 77-89.
- Hennig-Thurau, T., Aliman, D. N., Herting, A. M., et al. (2022). Social interactions in the metaverse: Framework, initial evidence, and research roadmap." *Journal of the Academy of Marketing Science*.
- Higgins, E. T. (2019). *Shared reality: What makes us stronger and tears us apart?* Oxford University Press.
- Hohenstein, J., Kizilcec, R., DiFranzo, D., Agharjari, Z., Mieczkowski, H., Levy, K., Naaman, M., Hnacock, J., & Jung, M. (2023). Artificial intelligence in communication impacts language and social relationships. *Scientific Reports*, 13, 5487. <https://doi.org/10.1038/s41598-023-30938-9>
- IBM. (2024). *Unlocking the power of chatbots; Key benefits for businesses and customers.* <https://www.ibm.com/think/insights/unlocking-the-power-of-chatbots-key-benefits-for-businesses-and-customers>
- Jager, J., Putnick, D., & Bornstein, M. (2017). More than Just Convenient: The Scientific Merits of Homogeneous Convenient Samples. *Monographs of the Society for Research in Child Development*, 82(2), 13-30.
- Kirk, H., Gabriel, I., Summerfield, C., Vidgen, B., Hale, S. (2025). Why human-AI relationships need socioaffective alignment. *Humanities and Social Sciences Communications*, 12, 728. <https://doi.org/10.1057/s41599-025-04532-5>

- Krippendorff, K. (2011). Computing Krippendorff's Alpha-Reliability. *Research at Penn Working Papers*, <https://repository.upenn.edu/handle/20.500.14332/2089>
- Krippendorff, K. (2019). *Content analysis: An introduction to its methodology* (4th ed.). SAGE Publications.
- Kvale, S., & Brinkmann, S. (2015). *Interviews: Learning the craft of qualitative research interviewing* (3rd ed.). SAGE Publications.
- Laapotti, T., & Raappana, M. (2022). Algorithms and organizing. *Human Communication Research*, 48(3), 491-515. <https://doi.org/10.1093/hcr/hqac013>
- Laestadius, L., Bishop, A., Gonzalez, M., Illenčik, D., & Campos-Castillo, C. (2022). Too human and not human enough: A grounded theory analysis of mental health harms from emotional dependence on the social chatbot Replika. *New Media & Society*, 26(10), 5923-5941.
- Lee, D., & Yoon, S. N. (2021). Application of artificial intelligence-based technologies in the healthcare industry: Opportunities and challenges. *International Journal of Environmental Research and Public Health*, 18, 271. <https://doi.org/10.3390/ijerph18010271>
- Lee, E. (2020). Authenticity model of computer-mediated communication: Conceptual explorations and testable propositions. *Journal of Computer-Mediated Communication*, 25(1), 60-73. <https://doi.org/10.1093/jcmc/zmz025>
- Liang, P., Bommasani, R., Lee, T., Tsipras, D., Soylu, D., et al. (2022). Holistic evaluation of language models. *arXiv*. <https://doi.org/10.48550/arXiv.2211.09110>
- Liao, Q. V., Subramonyam, H., Wang, J., & Wortman Vaughan, J. (2023). Designerly understanding: Information needs for model transparency to support design ideation for AI-powered user experience. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. 1-21.
- LivePerson. (2021). The digital lives of Millennials and Gen Z. *LivePerson*. <https://www.liveperson.com/blog/digital-lives-of-millennials-and-gen-z/#:~:text=Digital%20is%20the%20new%20IRL&text=In%20fact%2C%2065%25%20now%20communicate,and%20the%20UK%20at%2074.4%25>.
- MacQueen, K., McLellan-Lemal, E., Kay, K., & Milstein, B. (1998). Codebook Development for Team-Based Qualitative Analysis. *Field Methods*, 10(2), 31-36.
- Mahboudi, H., Farrokhi, F., & Ansarin, A. (2017). A Review on Application of Computers in Education Inside and Outside of Iran. *Advances in Language and Literacy Studies*, 8(4), 29-42.
- Mahmoudi, T., Ronaghi, M., & Amini, A. (2025). The Effect of Artificial Intelligence Adoption on Social Sustainability (Case Study: Isfahan Province Knowledge-Based Companies). *Journal of Entrepreneurship Development*, 17(4), 1-31.
- Malterud, K., Siersma, V., & Guassora, A. (2016). Sample Size in Qualitative Interview Studies: Guided by Information Power. *Qualitative Health Research*, 26(13), 1753-1760.

- Maples, B., Cerit, M., Vishwanath, A., & Pea, R. (2024). Loneliness and suicide mitigation for students using GPT3-enabled chatbots. *NPJ Mental Health Research*, 3(4), <https://doi.org/10.1038/s44184-023-00047-6>.
- Marcos-Pablos, S., & García-Peñalvo, F. J. (2022). *Emotional intelligence in robotics: A scoping review*. Cham: Springer.
- Marvin, M. (2006). *The emotion machine*. Hangzhou: Zhejiang People's Publishing.
- Matlabinejad, A., Fazeli, F. & Navaei, E. (2023). A systematic review of the promises and challenges of artificial intelligence for teachers." *Technology and Scholarship in Education*, 3(1), 23-44.
- McChesney, K., & Aldridge, J. (2019). Weaving an interpretivist stance through mixed methods research. *International Journal of Research and Method in Education*, 42(3), 225–238. McStay, A. (2018). *Emotional AI: The rise of empathic media*. London, Thousand Oaks, CA: Sage.
- McStay, A. (2020). Emotional AI and EdTech: Serving the public good? *Learning, Media and Technology*, 45, 270–283. <https://doi.org/10.1080/17439884.2020.1686016>
- Mijwil, M., Aggarwal, K., Mutar, D., Mansour, N., & Singh, R. (2022). The position of artificial intelligence in the future of education: An overview. *Asian Journal of Applied Sciences*, 10(2), 102–108.
- Morgan, D. (1997). *Focus groups as qualitative research* (2nd ed.). Sage Publications, Inc. <https://doi.org/10.4135/9781412984287>
- Morgante, E., Susinna, C., Culicetto, L., Quartarone, A., & Lo, B. V. (2024). Is it possible for people to develop a sense of empathy toward humanoid robots and establish meaningful relationships with them?" *Frontiers in Psychology*, 15, 1391832. <https://doi.org/10.3389/fpsyg.2024.1391832>
- Mostafa, G., Mahmoud, H., Abd El-Hafeez, T., et al. (2024). Feature reduction for hepatocellular carcinoma prediction using machine learning algorithms." *Journal of Big Data*. 11 (88). <https://doi.org/10.1186/s40537-024-00944-3>
- Nass, C., & Brave, S. (2005). *Wired for speech: How voice activates and advances the human-computer relationship*. Cambridge: MIT Press.
- Nass, C., & Moon, Y. (2000). Machines and mindlessness: Social responses to computers." *Journal of Social Issues*, 56(1), 81–103. <https://doi.org/10.1111/0022-4537.00153>
- O'Connor, C., & Joffe, H. (2020). Intercoder Reliability in Qualitative Research: Debates and Practical Guidelines. *International Journal of Qualitative Methods*, 19. <https://doi.org/10.1177/1609406919899220>
- Palinkas, L., Horwitz, S., Green, C., Wisdom, J., Duan, N., & Hoagwood, K. (2013). Purposeful Sampling for Qualitative Data Collection and Analysis in Mixed Method Implementation Research. *Administration and policy in mental health*. 42. <http://dx.doi.org/10.1007/s10488-013-0528-y>.
- Patton M. (2002). *Qualitative Research and Evaluation Methods* (3rd ed.). Sage.

- Patton, M. Q. (2015). *Qualitative research & evaluation methods* (4th ed.). SAGE Publications.
- Pentina, I., Hancock, T., & Xie, T. (2023). Exploring relationship development with social chatbots: A mixed-method study of Replika. *Computers in Human Behavior*, 140, 107600.
- Qadikolaei, M., Zali, N., Soltani, A. (2022). Spatiotemporal investigation of the digital divide, the case study of Iranian Provinces. *Environment, Development and Sustainability*, 26, 869-884.
- Raaijmakers, S. (2019). Artificial intelligence for law enforcement: challenges and opportunities. *IEEE Security & Privacy*, 17(5), 74-77.
- Raes, M., Meijerink, I., Lykourantzou, I., & Khan, V. (2024). For Explainable to Interactive AI: A Literature Review on Current Trends in Human-AI Interaction. *ArXiv*. <https://arxiv.org/html/2405.15051v1#bib.bib1>
- Rahimi, B. (2015). Rethinking Digital Technologies in the Middle East. *International Journal of Middle East Studies*, 47(2), 362-365.
- Rajabi, M., & Nasrollahi, M. (2023). The cultural impact of artificial intelligence development on social media in Iran. *Journal of Iranian Cultural Research*, 16(2), 95-125. <https://doi.org/10.22035/jicr.2023.3178.3481>
- Roberts, C. (2020). *Text analysis for the social sciences: methods for drawing statistical inferences from texts and transcripts*. Routledge
- Russell, S. (2019). *Human Compatible AI and the Problem of Control*. London: Penguin
- Sabbar, S., & Habib Zadeh Khiyaban, S. (2023). Algorithms of displacement: Emotional and rhetorical responses to ai-driven job loss in digital public discourse. *International Journal of Advanced Multidisciplinary Research and Studies*, 3(4), 1324-1331.
- Saldaña, J. (2021). *The coding manual for qualitative researchers* (4th ed.). Sage.
- Salehi, K., Habib Zadeh Khiyaban, S., & Sabbar, S. (2025). Artificial Intelligence and the Future of International Law and Power. *Journal of World Sociopolitical Studies*, 9(4), 923-958. <https://doi.org/10.22059/wsps.2025.401951.1552>
- Saunders, B., Sim, J., Kingstone, T., Baker, S., Waterfield, J., Bartlam, B., Burroughs, H., & Jinks, C. (2018). Saturation in qualitative research: exploring its conceptualization and operationalization. *Quality & Quantity*, 52(4), 1893-1907.
- Sharma, G. (2017). Pros and cons of different sampling techniques. *International Journal of Applied Research*, 3(7), 749 - 752.
- Sharp, C. (2003). Qualitative Research and Evaluation Methods. (3rd ed.) *Evaluation Journal of Australasia*, 3(2), 60-61.
- Sundar, S. (2020). Rise of machine agency: A framework for studying the psychology of human-AI interaction (HAI). *Journal of Computer-Mediated Communication*, 25(1), 74-88. <https://doi.org/10.1093/jcmc/zmz026>

- Sundar, S., & Chen, J. (2023). From CASA to TIME: Machine as a source of media effects. In A. Guzman, R. McEwen, and S. Jones (Eds.), *The SAGE handbook of human-machine communication*. Sage Publications.
- Sundar, S., & Lee, E. (2022). Rethinking communication in the era of artificial intelligence. *Human Communication Research*, 48(3), 379–385. <https://doi.org/10.1093/hcr/hqac014>
- Tai, M. (2020). The impact of artificial intelligence on human society and bioethics." *Tzu Chi Medical Journal*, 32(4), 339-343. http://dx.doi.org/10.4103/tcmj.tcmj_71_20
- Taylor, G. (2005). *Integrating quantitative and qualitative methods in research*. University Press of America Inc.
- Teddlie, C., & Tashakkori, A. (2009). *Foundations of mixed methods research: Integrating quantitative and qualitative approaches in the social and behavioral sciences*. SAGE Publications.
- Tracy, S. (2010). Qualitative Quality: Eight "Big-Tent" Criteria for Excellent Qualitative Research. *Qualitative Inquiry*, 16(10), 837-851.
- Tuckett, A. (2005). Applying thematic analysis theory to practice: A researcher's experience." *Contemporary Nurse*, 19(1), 75–87.
- Weber, A., Gupta, R., Abdalla, S., Cislighi, B., Meausoone, V., & Darmstadt, G. (2021). Gender-related data missingness, imbalance and bias in global health surveys. *BMJ Global Health*, 6, 007405. <https://doi.org/10.1136/bmjgh-2021-007405>
- Wei, J., Tay, Y., Bommasani, R., Raffel, C., Zoph, B., Borgeaud, S., et al. (2022). Emergent abilities of large language models. *arXiv*. <https://doi.org/10.48550/arXiv.2206.07682>
- Wiles, R. (2013). *What are qualitative research ethics?* Bloomsbury Academic.
- Wu, J. (2024). Social and ethical impact of emotional AI advancement: the rise of pseudo-intimacy relationships and challenges in human interactions. *Frontiers in Psychology*. <https://doi.org/10.3389/fpsyg.2024.1410462>
- Xiao, Z., Yuan, X., Liao, Q., Abdelghani, R., & Oudeyer, P. (2023). Supporting qualitative analysis with large language models: Combining codebook with GPT-3 for deductive coding. In *28th International Conference on Intelligent User Interfaces*, 75–78. ACM.
- Yin, R. K. (2018). *Case study research and applications: Design and methods* (6th ed.). SAGE Publications.
- Zhang, M., Tang, E., Ding, H., & Zhang, Y. (2024). AI in communication sciences and disorders. *ASHA journals*. Dataset. <https://doi.org/10.23641/asha.27162564.v1>