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Not All AI are Equal: Exploring the Accessibility of AI-Mediated Communication Technology

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ABSTRACT

While AI technologies and tools offer various potential benefits to their users, it is not clear whether opportunities to access these benefits are equally accessible to all. We examine this gap between availability and accessibility as it relates to the adoption of AI-Mediated Communication (AI-MC) tools, which enable interpersonal communication where an intelligent agent operates on behalf of a communicator. Upon defining six functional AI-MC types (voice-assisted communication, language correction, predictive text suggestion, transcription, translation, personalized language learning) we conducted an online survey of 519 U.S. participants that combined closed- and open-ended measures. Our quantitative results revealed how AI-MC adoption is related to software, device, and internet access for tools such as voice-assisted communication; demographic factors such as age, education and income in the case of translation and transcription tools; and some components of AI-MC literacy for specific functional tools. Our qualitative analyses provide additional nuance for these findings, and we articulate a number of barriers to access, understanding, and usage of AI-MC tools, which we suggest hinder AI-MC accessibility for user groups traditionally disadvantaged by one-size-fits-all technological tools. We end with a call for broadly addressing accessibility concerns within the digital technology industry.

AI is pervasive in our everyday lives. With the increasing adoption of AI systems in human-to-human interaction, technology's role in human communication is shifting from a passive to more agentic role. Interpersonal communication in which an intelligent agent operates on behalf of a communicator "by modifying, augmenting, or generating messages to accomplish communication goals" has been termed AI-Mediated Communication (AI-MC; Hancock et al., 2020, p. 1). AI systems may be integrated into hardware devices such as laptops, tablets, smartphones, smart speakers, or smartwatches, or they may be available as downloadable apps or software. Some examples include Amazon Alexa, Google Translate, Gmail Smart Reply, and Microsoft Word's spell check (Faggella, 2020). AI-MC tools serve a variety of different functions, including but not limited to interpreting and transmitting spoken messages, suggesting spelling and grammar corrections, providing auto-correct and auto-complete services, and facilitating communication across languages. Unlike human-machine communication, in which machines or AI systems are "communicative subject(s)" and "more than a channel or medium," such as social robots or chatbots (Eyssel & Hegel, 2012; Guzman, 2018; Krämer et al., 2012), AI-MC focuses on agentic channels and media where the AI system may not necessarily be considered another social actor.

Despite the extremely rapid development, implementation, and integration of AI systems in human communication, two basic questions still remain: Who uses these tools? More importantly, who does not use these tools, and why might this be? In this paper, we explore whether AI-MC technologies are "created equal"; in other words, we question whether AI-MC tools are equally accessible to all users and whether they afford equal usage regardless of a user's socioeconomic status, digital literacy, and digital skill levels.

In this paper, we use both quantitative and qualitative approaches to explore AI-MC adoption, access and literacy which allows us to articulate some of the previously underexplored ethical and social implications of these tools. Just as communication technologies have the potential to help actively mitigate human biases and reduce harm, it also

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has the potential to replicate and exacerbate these biases and harms (e.g. Benjamin, 2019; Suresh & Guttag, 2019). Moreover, there is a risk that AI-MC may systematically reproduce and deepen structural inequalities, especially pertaining to technological accessibility, depending upon the ways in which AI-MC technologies and tools are designed, implemented, and marketed.

1. Adoption of AI-MC tools

Hancock et al.'s (2020) conceptual piece proposes categorizing AI-MC tools by key features such as function, magnitude of the AI intervention, media types, optimization goals, autonomy, and role orientation. Relatedly, recent empirical work has investigated how these key features of AI-MC tools impact communication experiences such as language use and interpersonal perception. For instance, suggested text responses are purportedly optimized for "efficiency" in many cases (Henderson et al., 2017) but may have consequences on language production in terms of sentiment (Mieczkowski et al., 2021; Arnold et al., 2018, pp. 42–49). Other work has examined tensions in role orientation, where people may use AI systems to help them create online profiles, but the viewers of those profiles may feel like the creators are untrustworthy because of their use of AI (Jakesch et al., 2019). In this paper, we focus on *function*, using the example categories proposed in Hancock et al. (2020) as a starting point. To do so, we conducted a basic survey of existing AI-MC tool exemplars via internet search, using keywords "smart speaker products", "speech to text tools", "translation apps" (see Appendix). We ultimately developed a preliminary framework categorizing AI-MC tools into six types based on function (see Table 1). When we consider these diverse AI-MC types and their functions, it becomes clear just how omnipresent AI-MC, and AI more generally, can be in everyday life.

Table 1
Six functional categories of AI-MC.

Category	Main features	Sub-categories with examples
Voice-assisted communication	Respond to a sender's verbal command inputs in order to send or read messages.	Integrated software (Apple's Siri, Microsoft's Cortana, Google Assistant, etc.) Independent hardware devices (Google Home, Amazon Alexa, etc.)
Language correction	Identify errors in written text inputs and correct them, or suggest corrections which the sender can accept or reject.	Auto-correct (Apple iMessage Autocorrect, etc.) Spell- and grammar-check (Microsoft Word spell-check, Grammarly, Ginger, PaperRater, Google Docs proofreading, etc.)
Predictive text suggestion	Suggest text outputs in the form of words, phrases, and/or emojis, which the sender can accept or reject.	Reply suggestion (Gmail Smart Reply, Apple iMessage predictive keyboard, etc.) Sentence completion (Gmail Smart Compose, etc.)
Transcription	Convert messages from one modality to another.	Live dictation (Dragon, Apple Dictation, etc.) Audio to text and closed captioning (Otter.ai, Trint, Temi, Sonix, etc.) Text to speech (LiveTranscribe, NaturalReader, etc.) Audio description
Translation	Convert messages from one language to another, within or across modalities.	Live translation (Google "Translatotron") Text to text translation (Google Translate, etc.) Online bilingual dictionaries (Linguee, etc.) Subtitling
Personalized language learning	Help users become more proficient in non-fluent languages by personalizing instruction to the user's knowledge level.	Websites, apps, and programs (Duolingo, ELSA Speak, Rosetta Stone, Babel, Memrise etc.)

The first type, *voice-assisted communication*, includes tools which respond to a speaker's verbal commands in order to generate, send, or read messages, taking the form of integrated software such as Apple's Siri or smart speakers such as Amazon Alexa or Google Home. The second type of AI-MC falls under the category of *language correction*, which identify errors in written text inputs and correct them (or suggest optional corrections). This type includes integrated tools such as Apple iMessage's Auto-Correction feature, Microsoft Word's spell check, and Google Docs proofreading, as well as web applications such as Grammarly. The third type of AI-MC is *predictive text suggestion*, which includes reply suggestion tools such as Gmail Smart Reply and Apple iMessage's predictive texting keyboard, and sentence completion tools such as Gmail Smart Compose. The fourth and fifth types are *transcription* and *translation* tools. Transcription tools convert messages from one modality to another, as from speech to text (Dragon, Apple Dictation), text to speech (LiveTranscribe, NaturalReader), audio to text and closed captioning (Otter.ai, Sonix), and audio description tools. Translation tools convert messages from one language to another within or across modalities, as with text to text translation (Google Translate), live speech translation (Google's "Translatotron"), subtitling programs, and online bilingual dictionaries that use AI (such as Linguee). The final type of AI-MC tool consists of *personalized language learning* websites, apps, and programs such as Duolingo, ELSA Speak, and Memrise. These tools help users become more proficient in non-fluent languages by personalizing instruction to each user's knowledge level.

Although these six types differ in function and form, they all "by modifying, augmenting, or generating messages to accomplish communication goals" (Hancock et al., 2020). In order to understand how people use these various types of tools, we focus on the construct of adoption as applied to AI-MC, or an individual's propensity to use these new technologies (Porter & Donthu, 2006). As such, the first research question we ask is:

RQ1: What percentages of people adopt one or more of these six functional categories of AI-MC tools?

2. Access and AI-MC

Underlying adoption of AI-MC tools is the requirement of basic digital hardware, software, and internet *access*. As of 2019, 27 % of American adults did not have reliable high-speed broadband internet access at home, 19 % percent did not own a smartphone and 26 % did not report owning a desktop or laptop computer (Pew Research, 2019). Different demographic groups also experience disparities in internet and device access. Although gaps in internet and device adoption between different demographic groups have narrowed overall since 2000, internet, smartphone and laptop adoptions remain far from equal (Gonzales, 2015). For instance, Americans of older generations, lower income levels, and lower education levels are less likely to use the internet (Gonzales, 2015). Additionally, 92 % of White Americans reported using the internet in 2019, compared to only 85 % and 86 % of Black and Hispanic respondents, respectively (Gonales, 2015). As reflected by these demographic differences in internet usage, digital inequalities and disparities in technological access persist among people from less privileged societal contexts (Hargittai & Dobransky, 2017). These inequalities in device and internet access may themselves serve as barriers to AI-MC access.

Moreover, features of AI-MC tools and AI-MC-compatible devices themselves may be related to AI-MC access and therefore adoption. Many AI-MC tools come automatically integrated into popular technologies, while others require separate purchase. For instance, if a user chooses to enable Siri when setting up an Apple iOS device, the software is automatically activated on their device, requiring no further purchase or installation (Ritchie et al., 2019). However, tools such as Amazon's

Alexa and Echo series range from $50 to $200 (Amazon, 2020). Thus, we suspect that features such as the device compatibility of an AI-MC tool (i. e. whether it is integrated into commonly owned devices or not), its associated financial costs, and other factors all play a role in AI-MC access, and in turn AI-MC adoption. While these features may lend access in some cases, they might instead serve as barriers in others. In this study, we hypothesize:

H1: AI-MC access will be positively associated with AI-MC adoption as opposed to non-adoption.

H2: Socioeconomically privileged populations (i.e. those with higher levels of education and annual income), as compared to socioeconomically underserved populations, will have higher rates of AI-MC adoption as opposed to non-adoption.

3. Digital literacy and AI-MC

Digital literacy refers to the "ability to understand and use information from a variety of digital sources" (Bawden, 2008, p. 18). This definition concerns the functional and instrumental capacity of digital technology, as well as the ability of users to take full advantage of this capacity. Some scholars have widened the concept of digital literacy to incorporate elements of traditional media literacy and applied it to specific domains of technology adoption. For instance, Eshet (2004) suggests that digital literacy should be defined holistically, incorporating elements of socio-emotional literacy, information literacy, and photo-visual literacy. In the specific domain of web-oriented digital literacy, a functional, Internet and web skills-oriented definition is common (e.g. Hargittai, 2003; Hargittai & Dobransky, 2017).

More recent scholarship has applied a similar conception of AI literacy, which they define as "a set of competencies that enables individuals to critically evaluate AI technologies; communicate and collaborate effectively with AI; and use AI as a tool online, at home, and in the workplace" to the domain of AI (Long & Magerko, 2020, p. 598). This set of competencies is necessarily precluded by digital literacy and includes perceptions of key ethical issues surrounding AI, such as privacy, biases and harms, transparency, accountability, the ability to recognize AI, understand artificial "intelligence," and imagine possible futures for AI (p. 598).

Like Hargittai (2005; 2009), we are interested in the role that technological familiarity and understanding play in AI-MC adoption. How familiar are different users with different forms of AI-MC? How well do they feel they understand them? How might comfort using a tool and confidence that they can achieve a desired task affect AI-MC adoption? With these questions in mind, we suggest that a key component of AI-MC access, and in turn AI-MC adoption, is *AI-MC literacy*, or a user's level of familiarity (as a proxy for understanding), comfort, and confidence (as a proxy for skill) with individual forms of AI-MC, and with AI-MC tools as a subset of AI technology. By investigating the relationship between AI-MC literacy and adoption, we can gain a better understanding of how different users' experience levels and expertise with AI-MC tools may help, or alternatively hinder, their ability to access and take advantage of possible AI-MC benefits. We hypothesize that:

H3: All components of AI-MC literacy (i.e. familiarity, comfort, and confidence) will be positively associated with AI-MC adoption as opposed to non-adoption.

4. Barriers to AI-MC adoption, access, and literacy

Overall, we can think about potential barriers to AI-MC adoption, access and literacy through the framework of accessibility. "Accessibility" is a term with many definitions across different disciplines. In the literature of disabilities research, digital accessibility emphasizes the presence or absence of barriers that affect people's ability to access and use certain tools, services, or technologies (Kulkarni, 2019). A broader approach discusses the importance of "[taking] into account issues related to literacy, availability of technology, digital technology, [and] the use of minority languages; " such an approach can be understood as an appeal to "universal accessibility" (Abascal et al., 2015, p. 1).

Considering these, we conceptualize ***AI-MC accessibility*** as the absence of barriers to AI-MC adoption, access, and literacy. This concept combines broad understandings of "universal accessibility" with the narrower, barriers-focused perspective of accessibility within the disabilities literature. Keeping this notion of AI-MC accessibility central to ultimate AI-MC adoption, we therefore ask:

RQ2: What barriers, if any, could be removed to help people better access, use, and understand different types of AI-MC?

5. Methods

5.1. Participants

We conducted an online survey on Amazon Mechanical Turk, a crowdsourcing platform that allows researchers to collect data from people with various demographics or behavioral characteristics. For our study, participants within the United States who had completed more than 5000 hits and had a 95 % and above approval rate were eligible to participate in the survey. Responses were collected until we reached our target sample size of 500, allowing us to detect a small effect size with power = .80. We received a total of 535 responses, and excluded 16 participants who completed the study within a minute or provided nonsensical short answer responses (e.g. defining irrelevant technological terms, repeating the same answer, or listing the names of online survey-hosting platforms). The final sample size was 519.

Participants were between the ages of 19 and 74 years ($M = 38.41$, $SD = 12.18$, 54.4 % male, 45.2 % female, 0.4 % nonbinary). They were sampled from across the United States, representing reasonably though imperfectly diverse ethnic and socioeconomic backgrounds. Of our participants, 97.3 % spoke English as their native language. The majority (75.2 %) of our sample self-identified as "White, Caucasian, or European American," compared to the 76.3 % of Americans who identified as white alone in 2019 (U.S. Census Bureau [USCB], 2019). Of the remaining 24.8 % of participants, 10.3 % identified as "Asian or Asian American" compared to the 2019 parameter of 5.9 % Asian alone (USCB); 7.6 % identified as "Black, African American, or African" compared to 13.4 % Black alone (USCB, 2019); 6.0 % identified as "Hispanic, Latinx, or Spanish origin" compared to 18.5 % Hispanic or Latino alone (USCB, 2019); and 0.6 % identified as "Native American or Pacific Islander" compared to 1.5 % alone (USCB, 2019). All of our participants had, at minimum, a high school diploma or GED, and the most commonly represented level of education (45.8 %) was a four-year college degree; in 2019, only 22.5 % of all American adults aged 25 and older had completed at least a four-year college degree (UCSB, 2020a). Finally, our sample's median annual income mode fell within the range of $50,000 to $74,999. 10.9 % of our participants have a family income of less than $25,000; 11.7 % have a family income between $25,000 to $34,999; 18.6 % have a family income between $35,000 to $49,999; 22.2 % have a family income between $50,000 to $74,999; 11.7 % have a family income between $100,000 to $149,999; 4.2 % have a family income between $150,000 to $199,999; and 2.9 % have a family income of $200,000 or more. In 2019, the median annual household income in the United States was $68,703 (UCSB, 2020b).

5.2. Measures

AI-MC adoption: We asked if participants had ever used each of the six aforementioned categories of AI-MC tools (Table 1). For example, for "language correction tools", we asked participants: "Have you ever used any proofreading and auto-correct tools such as Apple's iMessage autocorrection, and/or spell-check and grammar-check tools such as Grammarly, Ginger, Paper Rater, Microsoft Word spell-check, or Google Docs proofreading?" with response options of Yes or No.

AI-MC literacy: We adapted an established digital literacy scale from previous studies (Hargittai, 2009) to measure three dimensions of AI-MC literacy: familiarity (α = 0.84), comfort (α = 0.83), and confidence (α = 0.84; all α are Cronbach's alpha). This scale included six sets of the following three questions, focused on one of the six AI-MC types. Each of the six sets of questions provided space for participants to answer specifically about individual subcategories of AI-MC within each AI-MC type, as shown in Table 1. See Appendix 1 for questions and scales.

AI-MC device access: We asked participants how many internet-accessing devices, if any, they had reliable access to (mobile smartphone, tablet, personal computer, or other). We summed the number of devices they had to calculate the device access score.

AI-MC barriers: We used open-ended questions to explore the barriers that participants may face regarding AI-MC adoption. All participants were asked the following: 1) "Overall, what are your thoughts about the technologies and tools you indicated use of in this survey?" 2) "What barriers, if any, could be removed to help you better access, use, and understand the technologies and tools discussed in this survey?" and 3) "What concerns, if any, do you have about using these kinds of AI technology?"

6. Analytical approaches

We used a basic descriptive analysis and binary logistic regressions to explore responses to closed-ended questions and respond to RQ1, and H1, H2, and H3. We applied grounded theory (Strauss & Corbin, 1994) and used thematic coding methods (Gibbs, 2007) to analyze open-ended data for RQ2. We first randomly extracted 15 % of the quotes from the data to identify themes concerning AI-MC adoption barriers. Once the initial themes were formed, we applied thematic coding to all data to strengthen and finalize the themes. This enabled identification of emerging themes in the data and allowed us to uncover perceptions and barriers that prevent or deter AI-MC access, understanding, and adoption, complementing our quantitative findings.

6.1. Quantitative results

Our first research question (RQ1) concerned overall patterns of adoption of the six functional AI-MC types. We conducted a basic descriptive analysis and found that the most widely adopted AI-MC tools are those pertaining to voice-assisted communication, followed by language correction, predictive text suggestion, translation, personalized language learning, and transcription tools, as shown in Table 2.

All but 5 of our survey respondents (0.96 %) reported having used AI-MC pertaining to at least one of the six categories; in other words, 99.04 % of participants were familiar with at least one form of AI-MC. We also investigated the connections among demographic variables, access and literacy variables (see Table 3). Notably, age is generally significantly inversely related to AI-MC tool adoption, regardless of tool type. Further, the increased feelings of comfort, one element of AI-MC literacy, had significant positive correlations with all tool types.

In H1, we predicted that device access ($M = 2.56$, $SD = 0.68$ number of devices) would be positively associated with the adoption of the six different functional types of AI-MC tools, as opposed to non-adoption. We conducted a series of binary logistic regressions with each type of AI-MC tool adoption as the dependent variable to test this hypothesis (see Table 4). For voice-assisted communication tools, the regression was significant [χ^2 (9, 514) = 53.82, $p < .001$] and revealed that for this type of AI-MC, the number of internet-accessing devices available to a user was positively related to adoption (b = .49, $p < .05$). For the five remaining types (language correction, predictive text suggestion, transcription, translation and personalized language learning) of AI-MC tools, we did not find a significant association between number of devices and adoption (see Table 4). Thus, our hypothesis that AI-MC access would be positively connected to AI-MC adoption was supported only in the case of voice-assisted communication AI-MC tools.

Furthermore, we predicted that socioeconomically privileged populations (i.e. those with higher levels of education and annual income), as compared to socioeconomically underserved populations, would have higher rates of AI-MC adoption as opposed to non-adoption. We entered the demographic variables of age, gender, ethnicity, education, and income into the same regression as above, revealing that demographic considerations were significantly related to the adoption of two of our six AI-MC types (see Table 4). First, the regression showed that for transcription tools [χ^2 (9, 514) = 60.62, $p < .001$], younger participants were significantly more likely to adopt transcription tools than older participants. Moreover, education and income were shown to be significantly connected to the adoption of translation tools [χ^2 (9, 514) = 39.05, $p < .001$]. Participants with higher education and with lower annual family income were significantly more likely to use translation tools than participants with lower education and higher family incomes, indicating that H2 was partially supported.

Finally, in H3 we predicted that All components of AI-MC literacy (i.e. familiarity, comfort, and confidence) would be positively associated with AI-MC adoption as opposed to non-adoption. After entering the three dimensions of AI-MC literacy (familiarity: $M = 3.56$, $SD = 0.77$; comfort: $M = 3.63$, $SD = 0.87$; confidence: $M = 3.52$, $SD = 0.83$) into our logistic regression, we found that for the adoption of voice-assisted communication tools [χ^2 (9, 514) = 53.82, $p < .001$], language correction tools [χ^2 (9, 514) = 33.67, $p < .001$], predictive text suggestion tools [χ^2 (9, 514) = 39.66, $p < .001$], and personalized language learning tools [χ^2 (9, 514) = 69.18, $p < .001$], comfort was a significant predictor of adoption. As such, for four out of six AI-MC categories, when participants believed that they felt comfortable using a tool, they were more likely to adopt an AI-MC tool (see Table 4).

When it came to translation tools [χ^2 (9, 514) = 39.05, $p < .001$] and personalized language learning tools [χ^2 (9, 514) = 69.18, $p < .001$, we found that familiarity was a significant predictor of adoption (see Table 4). We did not find the adoption of transcription tools to be significantly connected with any of the three dimensions of AI-MC literacy, nor did we find that confidence using the tools was significantly connected with the adoption of any AI-MC tool type. Thus, H3 was supported in certain cases, depending upon the type of AI-MC tool and the components of AI-MC literacy in question.

Table 2
AI-MC adoption by functional category.

AI-MC type	% of participants who indicated adoption
Voice-assisted communication	91.94 %
Language correction	91.78 %
Predictive text suggestion	80.50 %
Transcription	41.30 %
Translation	70.17 %
Personalized language learning	57.17 %

6.2. Qualitative results

Analysis of the 519 open-ended responses to the survey questions revealed several notable themes with regards to AI-MC accessibility and adoption. The analysis shed particular light on access, demographic, and AI-MC literacy barriers, as well as user experiences with AI-MC tools and technologies more generally (RQ2). These findings also provided compelling support for many of our quantitative findings. We found that device and internet access (including tool-device compatibility and cost concerns), demographic factors (namely age and speech characteristics), and AI-MC literacy (especially concerns about comfort) each suggested different affordances of and hindrances to ultimate AI-MC tool adoption.

6.2.1. Barriers related to device, internet, and AI-MC access

Although every respondent reported having used at least one out of the six types of AI-MC, our analysis revealed common barriers relating to

Table 3
Pearson correlations among demographic variables, AI literacy, and AI-MC tools adoptions.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Age (continuous)	1													
2. Gender (categorical)	.06	1												
3. Ethnicity (categorical)	-.20**	-.06	1											
4. Education (categorical)	.05	.03	-.01	1										
5. Income (categorical)	-.02	-.03	-.02	.36**	1									
6. Device Access (continuous)	.10*	-.06	-.02	-.04	.14**	1								
7. Familiarity (continuous)	-.23**	-.03	.07	-.06	.03	.14**	1							
8. Comfort (continuous)	-.29**	-.09*	.10*	.02	.13**	.18**	.73**	1						
9. Confident (continuous)	-.27**	-.08	.07	-.03	.08	.13**	.66**	.80**	1					
10. Voice Assistant (categorical)	-.12**	-.05	.04	.07	.15**	.16**	.14**	.29**	.24**	1				
11. Language correction (categorical)	-.06	.04	-.01	.09*	.08	.03	.08	.21**	.16**	.12**	1			
12. Predictive text (categorical)	-.27**	-.04	-.00	.07	.12**	.11*	.14**	.24**	.19**	.23**	.22**	1		
13. Transcription (categorical)	-.23**	.01	.12**	.03	.08	.03	.24**	.28**	.23**	.15**	.15**	.19**	1	
14. Language learning (categorical)	-.26**	.00	.04	.06	.02	.05	.32**	.34**	.30**	.16**	.18**	.15**	.22**	1
15. Translation (categorical)	-.11**	-.07	.02	.04	-.04	.09	.24**	.21**	.19**	.13**	.16**	.10*	.21**	.15**

Note: ** indicates the correlation is significant at the 0.01 level (2-tailed); * indicates correlation is significant at the 0.05 level (2-tailed).

Table 4
Access, demographic, and literacy variables predicting AI-MC adoption, relating to hypotheses H1, H2 and H3, respectively.

	Voice assist.	Proofreading	Text suggest.	Transcription	Translation	Language learning
Demographics						
Age	0	.001	0	**-.03***	.001	0
Gender	-.12	.37	.02	.21	-.22	.11
Ethnicity	.06	-.03	.01	.08	-.003	.01
Education	.03	.22	.06	.08	.19*	.14
Income	.20	.07	.14	.06	-.13*	-.04
Tech access						
# of devices	**.49***	.004	.22	.03	.23	.02
AI-MC Literacy						
Familiarity	-.50	-.49	-.18	.24	.51*	**.50***
Comfort	**1.20***	**1.41***	**.80***	.41	.17	**.43***
Confidence	.19	-.26	-.05	0	.08	.17
Nagelkerke's R^2	.23	.15	.12	.16	.11	.17

Note: * and bolded text indicates $p < .05$.

devices and internet access that may have hindered AI-MC adoption. First, tool-device compatibility was noted as a barrier. Several participants worried that they were unable to access certain types of AI-MC tools, or that they would lose existing access, due to outdated or incompatible devices. A white, female participant in her 30s with an annual household income between $75,000 to $99,000 wrote that "Adapting to new technologies that come out [is one concern of mine;] what if my device becomes outdated [?]"

A second barrier participants noted was cost. Some respondents suggested the lowering or even removal of the cost barrier associated with certain AI-MC tools; for example, an Asian woman in her 30s with an income range of $35,000 to $49,999 noted: "I think that removing the fees or prices to some of these tools would be beneficial for some users that really need them like students, teachers, and parents." These points were echoed by other participants, who cited concerns that the devices needed to access AI-MC tools are often too costly to justify purchasing.

Aside from digital devices themselves, having a strong and sufficiently stable wifi connection also ensures that people are able to access and use AI-MC tools, the vast majority of which require an internet connection to properly work (with the exception of Microsoft Word's spelling correction, among other tools). For some communities, there may not be broad-enough access to quality internet for affordable prices. For others, internet-related frustrations when using AI-MC technologies involve spotty or unstable internet when they are on the move. An Asian male participant in his 20s wrote: "I think these technologies and tools should be able to function better when the internet connection is weak. That's the only barrier I face." Additionally, a Black female participant in her 20s shared that she would benefit from "having more access to these technologies offline and in more places."

6.2.2. *Barriers related to demographics*

In addition to access barriers, barriers related to user demographics may play a role in who does or does not adopt different AI-MC types. Our analysis reveals two primary recurrent themes related to demographics: age and English language biases.

6.2.2.1. Age. A few types of concerns surrounding age and AI-MC adoption arose in our data. Firstly, of the participants who expressed concerns relating to age, most tended to belong to older generations. Some respondents noted that newer technologies are too confusing and complicated for older people to use effectively. For instance, a white woman in her 60s stated that "since [she is] older, [she] find[s] that the new technologies are too complicated." Further, other respondents noted older generations might not even know that these resources are available for them. A white woman in her 40s pointed out that: "Sometimes older generations … [are] anxious about new technologies. It would be nice if they could be introduced to these things in structured settings and shown what kinds of things they can accomplish with them."

6.2.2.2. English language and Non-"Standard" speech biases. English is the default language for which most AI-MC tools function. Although the vast majority (97.3 %) of our sample spoke English as their native language, comments from non-native and native English speakers alike suggested that participants may be more willing to use these tools if their services are available in their native languages and are able to understand various accents, particularly in relation to voice-assistant technology. For instance, one 20-year-old Asian male wrote that they "would use all voice assistants more if they were available in my native language."

Moreover, it appears that current voice recognition technology still struggles to accurately recognize different accents, tones of voice, and speech differences. These concerns cut across tools which often utilize speech recognition. One white, bilingual man fluent in English and Japanese pointed out that he was concerned about "inaccuracies and misunderstandings in the case of text transcription or translation [and inability] to use speech recognition due to having an accent." Further, a male Latino participant commented that speech-related tools could be improved "if they were able to understand different accents better." Monolingual and multilingual participants alike commented variously about the need for AI-MC tools to better detect "inflections," "volumes," "different accents, styles, and disabilities," and other "variations in speech," suggesting that non-native English speakers, or English speakers of minoritized dialects or abilities may face hurdles when using certain AI-MC tools.

6.2.3. Barriers related to AI-MC literacy

Finally, our qualitative analysis explored the relationship between AI-MC literacy and AI-MC adoption. Our findings reflect the three main dimensions of AI-MC literacy: understanding, confidence, and comfort. On one hand, some respondents mentioned that the tools listed in our survey were easy to use. For example, a Black man in his 30s said, "I've typically been able to figure out how to use these tools successfully, without many issues, if at all, and have always found them easy to utilize, once understood." Yet many individuals felt that certain AI-MC tools were difficult to understand and lacked confidence in using them. For example, a white woman in her 50s commented, "I think I lack some experience in technologies simply because I don't know they are available." Notably, this complements older participants' concerns that AI-MC is not as well-marketed to older users, connecting this lack of visibility to a lack of opportunities to develop technological confidence.

Finally, participants in our survey provided mixed responses when it came to comfort using AI-MC tools. Some respondents showed strong positive feelings based on their experiences of use. One white woman in her 60s said that "Siri can be my best friend" revealing that participants sometimes felt strong interpersonal-like relationships with the tools. However, digital privacy has remained a large and contentious issue (Acquisti et al., 2015), which was reflected by participants' expressions of discomfort and distrust towards certain types of AI-MC. For example, a white man in his 50s explained how issues of privacy affected his personal view of AI-MC by saying: "The companies who produce these pieces of technology would have to make great strides and show a real commitment to protecting users security and privacy before I would adopt these technologies more wholeheartedly."

One final, oft-repeated concern that hindered comfort for participants dealt with fears about implicit biases embedded in AI-MC and hidden motives of the companies responsible for various AI and AI-MC tools. However, participants seemed split on the question of whether systemic biases — those extending beyond individual creator or programmer teams — might end up influencing how users interact with AI and AI-MC tools. For instance, a white man in his 30s said:

I'm mostly concerned that various AI's have implicit biases baked in by their creators and they will lead me to act in ways that I don't fully understand or reinforce stereotypes that exist in our society. I also worry that the AIs have ulterior motives and will try to lead me to do things that I wouldn't otherwise that will benefit their creators.

Moreover, one Black man in his 20s commented, "I fear that AI technologies may… Discriminate and show prejudice towards marginalized people." Other participants, such as a white woman in her 40s, suggested in contrast: "AI technology can help do things in precise, consistent ways without the bias of a human."

7. Discussion

While AI technologies and tools offer various potential benefits to their users - from reducing human error and increasing task efficiency, to facilitating online decision-making and interpersonal communication (e.g. Hancock et al., 2020; Pew Research, 2018) - it is not clear whether these benefits are equally accessible to all. Our paper builds on literature regarding technological adoption, access, digital literacy and accessibility (e.g. Eshet, 2004; Gonzales, 2015; Hargittai & Dobransky, 2017), applying it to the relatively nascent field of AI-MC by investigating the underpinnings of technological adoption across six AI-MC types.

7.1. Unequal adoption across AI-MC tool types

Our study demonstrates that not all AI-MC tools are "created equal" in regard to several dimensions. First, there are a number of different types of AI-MC, which are adopted differently by users overall. In choosing to group AI-MC tools by function (Table 1), our study reveals that AI-MC technology is not a monolith; each functional type takes different forms, and each mediates interpersonal communication in different ways. Moreover, AI-MC tools are not *used* equally. The most commonly adopted AI-MC type appears to be voice-assisted communication (e.g. Amazon Alexa), followed very closely by language correction tools (e.g. Apple iMessage Autocorrect, Grammarly); approximately 90 % of our sample indicated having used both types. Notably, these two AI-MC types include tools built into various devices as well as tools that can be purchased separately. Voice-assisted communication tools might be most commonly adopted because they are capable of functions beyond AI-MC. Many participants explicitly noted how tools like Siri and Alexa are useful for completing various tasks, a finding which has been corroborated in relevant literature; for example, a study of voice assistants by Ammari et al. (2019) found that participants provided over 193, 000 commands for Alexa.

Moreover, predictive text suggestion tools (e.g. Gmail Smart Reply), translation tools (e.g. Google Translate), and personalized language learning tools (e.g. Duolingo) were also used by a majority of participants. Results from our correlations analyses also indicate that adoption of one type of tool is related to adoption of other tools (see Table 3). However, transcription tools, such as Otter. ai, were the only AI-MC tool type used by a minority of participants. It is possible that the qualitative trends observed regarding barriers to access — such as associated cost, lack of visibility, and concerns about tool-device compatibility — could help explain these relative adoption rates.

7.2. Demographic variables and AI-MC adoption

In addition to factors related to AI-MC access, a number of demographic factors are associated with AI-MC adoption. Among those implicated in this study are education, household income, age, and speech characteristics. First and foremost, our quantitative data reveals that users' highest level of education is positively correlated with their adoption of translation tools. The more educated a person is, the more likely they are to have used translation tools. However, our data shows a negative relationship between income and translation tool adoption; the higher a person's income, the less likely they are to have used translation tools. The negative connection between family income and the use of translation tools might be explained by an occupation income bias; the occupations that require translation assistance, such as service industries, may not provide high income (see U.S. Bureau of Labor Statistics, n. d.). Future studies may explore the nuanced relationship between user demographics and the adoption of specific AI-MC types.

Our study also found that for transcription tools (e.g. Otter. ai), age was a significant predictor of adoption: the older a person is, the less likely they are to use these tools. The results of our correlation and qualitative analyses support and broaden this finding, demonstrating that older age can be a barrier to AI-MC access across the board, given that many users perceive that AI-MC tools are less visibly marketed and explained to older demographics. Our results also suggest that older age is connected with increased difficulty understanding AI-MC and how to use it, as many older participants expressed concerns about the confusing, complex, and often incomprehensible nature of AI-MC tools. Other related work has found similar concerns, noting the "disempowerment" older adults may feel when interacting with digital technologies (Hill et al., 2015). The companies who create and market AI-MC tools may not sufficiently factor considerations about older populations into account, resulting in unique digital challenges for older users.

Correspondingly, our participants' comments indirectly suggest that younger users may be advantaged when it comes to AI-MC usage and understanding. This notion is well-supported in the literature when it comes to digital technology adoption, based on work surrounding "digital natives" and their advantageous familiarity with digital technology (Hargittai, 2010). Thus, age and the ways in which the technological industry caters to younger people may facilitate AI-MC adoption in younger populations, just as these factors can inhibit older populations who may lack the time, guidance, resources, or access to initiatives with which to gain the knowledge and skill necessary for comfort with, and understanding of, AI-MC tools.

Moreover, our study finds that language and speech characteristics can serve as a barrier or aid to AI-MC adoption, depending on the user. Not only is English the default language for many AI-MC tools, but users also reported concerns about how accents, slurred speech, different styles and dialects, and other "non-standard" features of their and others' English speech seemed to present a barrier to usage for certain AI-MC tools. These specifically include voice-assisted communication and speech-to-text transcription, and some translation tools. Our study reveals that even users who perceive their English speaking as "standard" and "unaccented" recognize the subtle, yet impactful barriers that "non-standard" English speakers disproportionately face when using certain AI-MC tools, building on findings in both news media and recent academic work (e.g. Benjamin, 2019; Rangarajan, 2021).

7.3. Barriers related to access

Our results suggest that AI-MC tool access (as a function of device access and internet access) does indeed play a role in AI-MC tool adoption, particularly in the case of voice-assisted communication tools. Given that devices such as Amazon Alexa and Google Home are reliant upon an internet connection to work (Miller, 2020; Snead, 2020), as are software programs like Siri (Owen, 2018), it follows that voice-assistant communication adoption is significantly linked to internet-accessing device access. Our analysis of open-ended responses also revealed that many participants expressed concerns about their devices becoming outdated and incompatible with new AI-MC tools, as well as a number of internet-related frustrations, such as a lack of access to affordable — or otherwise stable and consistent — internet with which to utilize AI-MC tools. Thus, our study suggests that not only are AI-MC not adopted equally, they also are not equally accessible to all users on the basis of device access, internet access, and the cost of device, internet, and AI-MC services.

7.4. AI-MC literacy

Finally, our results suggest that AI-MC literacy, particularly the dimensions of comfort and understanding, is positively connected to AI-MC adoption. This suggests that lower degrees of AI-MC literacy, especially lower levels of understanding and comfort using AI-MC, can act as barriers to adoption. In other words, AI-MC is not experienced equally by all users. Comfort using AI-MC tools was found to be positively related to the adoption of all AI-MC types with the exception of transcription and translation tools. Given the prominence of comfort when it comes to AI-MC adoption, our qualitative findings lend a more fine-grained perspective into how comfort, or lack thereof, can influence how users think about, feel, understand, and use AI-MC. Some noted that they experienced positive affective feelings towards and about AI-MC, while others cited concerns about privacy and implicit bias built into AI-MC tools. These experiences are in line with perceptions of other types of systems that rely on AI as well, such as social robots or recommendation algorithms (e.g. Araujo et al., 2020; De Graaf & Allouch, 2013; Lutz et al., 2019; Shyong et al., 2006, pp. 14–29).

Moreover, users' self-reported level of familiarity was found to be positively connected to their adoption of two of the six AI-MC types: translation and personalized language learning tools. Interestingly, both of the latter tools help users learn, send messages, and receive content across languages, suggesting that an understanding of AI-MC tools themselves is especially important when it comes to communication across languages. Correlation analyses supported this finding, but participants' open-ended responses were mixed, aligning with other calls for producers of AI-MC tools to make their products more straightforward and explainable to users of all backgrounds (e.g. Wang et al., 2019), particularly translation and personalized language learning tools.

7.5. Improving AI-MC accessibility

Just as AI-MC is a distinct class of AI technology, the six functional types of AI-MC defined in this paper are distinct from one another. People use and think about them differently, and different populations face unique combinations of barriers when it comes to different types. We have conceptualized the overall presence (or absence) of these barriers as AI-MC accessibility. When AI-MC accessibility is taken into account, individuals have more freedom to access, use, and understand different tools according to their own needs and preferences. When companies reduce hurdles to technological adoption, improve the marketing of products across the board, and build in affordances for those who are traditionally disadvantaged by one-size-fits-all technologies, they approach an equity of accessibility across all potential users.

7.6. Limitations

Our study has several important limitations. The first is our recruitment of participants from Amazon Mechanical Turk. Although they are a valid research population (Berinsky, Huber, & Lenz, 2012; Hauser & Schwarz, 2016), our sample was not perfectly representative of the United States population. Specifically, our sample slightly over-represented white and Asian Americans, Americans residing in the southern states, and Americans with higher education levels. Future research should correct for these imbalances by focusing on underrepresented groups in order to advance our understanding of AI-MC accessibility, literacy and adoption.

Second, our qualitative results revealed mixed confidence assessments from participants, who cited a lack of visibility or habitual use as primary reasons for low confidence. However, our study did not reveal any statistically significant associations between confidence and AI-MC adoption. While this may reflect the absence of a connection between the two variables, it is also possible that this gap in our findings derives from the wording of our survey question itself (Appendix 1). Digital skill, for which we intended confidence as a proxy, is infamously difficult to measure indirectly (Hargittai, 2005, 2009). Perhaps, as Hargittai (2009) suggests, asking people to rate their level of understanding of a constrained number or type of digital tools and terms is a better proxy for skill than traditional measures of self-perceived skill, like self-efficacy.

Third, it is important to note that our study does *not* imply a causal relationship between AI-MC adoption, access and literacy. For instance, it is possible that higher levels of AI-MC literacy along any combination of dimensions may help users overcome common barriers to AI-MC understanding and usage, or it is possible that the more an individual uses AI-MC, the more comfortable, confident, and knowledgeable they become. Alternatively, there may be additional unexplored factors which are causally related to both AI-MC literacy and adoption. Our qualitative responses raised a number of possible avenues for further research, such as the intersections between disability and AI-MC adoption, affective responses to and interpersonal-like relations with AI-MC tools (particularly voice assistant technologies), privacy concerns and distrust surrounding AI-MC tools, and perceptions and realities of implicit AI-MC biases.

7.7. Conclusion

The present study suggests that AI-MC is neither equally accessible nor equally impactful to all. Through closed- and open-ended measures regarding six functional AI-MC types, we examined how AI-MC adoption is related to AI-MC access, AI-MC literacy, and demographic factors. Our findings provide quantitative evidence for connections between AI-MC access and adoption in the case of voice-assisted communication tools, AI-MC literacy and adoption for several types of tools, as well as demographic variables like higher education and lower annual family income with adoption of translation tools. Further, we qualitatively demonstrate support for these findings, as well as key areas for future research.

Credit author statement

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Appendix

1) We used the following list of internet search keywords, then proceeded to use related words and phrases suggested by Google: “tools like Siri”, “tools like grammarly, “spellcheck tools”, “tools like gmail smart reply”, “dictation programs”,"audio to text tools”, “transcription tools”, “translation programs”, “language learning apps”, “bilingual dictionary online”, “live translation tools”, “closed captioning programs”,"programs like duolingo”
2) Complete 5-point scales for questions measuring 3 dimensions of AI-MC literacy:

Familiarity/Understanding—*“How well do you feel you understand each of the following tools?”* (1-No understanding, 2-A little understanding, 3-Some understanding, 4-A lot of understanding, 5-Full understanding.)

Comfort—*“How comfortable do you feel using each of the following tools?”* (1-Not at all comfortable, 2-Slightly comfortable, 3-Moderately comfortable, 4-Very comfortable, 5-Extremely comfortable.)

Confidence/Skill—*“When using each of the following tools, how confident are you that you can accomplish what you’re trying to achieve?”* (1-Not at all confident, 2-Slightly confident, 3-Moderately confident, 4-Very confident, 5-Extremely confident.)

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