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Exploring the association between use of conversational artificial intelligence and social capital: Survey evidence from Hong Kong

Yu-Leung Ng
Hong Kong Baptist University, Hong Kong

Abstract
Media use–social capital research has studied traditional and social media use and associated social capital. Still, little is known about whether social capital would be cultivated or damaged by the use of conversational artificial intelligence (AI). This study explores the associations between conversational AI use and various measures of social capital using a territory-wide survey of an online representative sample in Hong Kong ($n = 1022$). The results showed that conversational AI users ($n = 398$) were more likely to have more offline and online bonding and bridging social capital, social trust, and civic participation than non-users ($n = 624$). For the conversational AI users, intensity and frequency of conversational AI use were the positive predictors of the social capital measures. The findings demonstrated larger effect sizes for online bonding and bridging social capital than offline bonding and bridging social capital.

Keywords
Artificial intelligence, computers are social actors, conversational AI, human–AI interaction, human–machine communication, social capital

Communication researchers have been interested in studying the association between media use and social capital. The first era of media use–social capital research investigated the negative influence of traditional media consumption (particularly television

Corresponding author:
Yu-Leung Ng, Department of Journalism, School of Communication and Film, Hong Kong Baptist University, Room 933, Communication and Visual Arts Building, 5 Hereford Road, Kowloon Tong, Kowloon, Hong Kong.
Email: yuleungng@hkbu.edu.hk

exposure) on social capital (Putnam, 1995). The second era of research studied the relationship between Internet use (particularly social media use) and social capital. A large corpus of research has empirically demonstrated a positive linkage between use of social network sites and social capital (Ellison et al., 2007; Valenzuela et al., 2009). Little is known about whether social capital would be cultivated or vandalized by the use of communicative artificial intelligence (AI) in the latest era. This study intends to explore conversational AI use and associated offline and online bonding and bridging social capital, social trust, and civic participation. This study was conducted through a territory-wide survey of an online representative sample in Hong Kong.

AI is broadly comprehended as a design of human intelligence within a machine that can execute a certain level of human intelligence (Frankish and Ramsey, 2014). Specifically, communicative AI refers to the new media technologies devised to perform designated tasks as the communicators that were originally processed by and stinted to humans (Guzman and Lewis, 2020). Communicative technologies executing a limited range of communication existed before communicative AI. However, communicative AI learns to automatize communicative functions through computational algorithms of natural language processing. Communicative AI has the ability to communicate with humans in natural language. This study focused on one type of communicative AI that functions as communicators—conversational AI that can vocally respond to human requests, such as Apple Siri, Google Assistant/Home, and Amazon Alexa. People can talk to these voice-based virtual assistants, which are fixtures in mobile devices, an integration into desktops and laptops, or smart assistants for users' homes (Guzman, 2019).

This study is important because more and more individuals communicate with human-like virtual assistants due to the navigation of conversational AI for everyday life (Guzman, 2019). The time displacement hypothesis (Nie, 2001; Putnam, 2000) suggests that people spend most of their leisure time privately at home watching television and using the Internet, so they engage less in civic participation and then lack social support and interpersonal trust. It is thus possible that people are increasingly speaking with conversational AI and are decreasingly initiating, building, and maintaining social capital. In contrast, the computers are social actors approach (Nass et al., 1994) posits that people could apply some of the similar social rules that are used with other people to interact with media technologies. Interactions with sophisticated media technologies (e.g. conversational AI) may relate to an enhancement in social interactions with other people (Nass and Yen, 2010), and thus can facilitate social capital. Studying whether conversational AI use would erode or construct social capital would be significant.

Definitions of social capital

Social capital is defined as the resources created through individuals' social interactions (Coleman, 1988; Putnam, 2000). Similar to financial capital, social relations embedded in individuals' social networks can be treated as an investment with anticipated returns in the future (Lin, 2001). Putnam (2000) proposed that social capital involves both the social networks and the outcomes of the networks, such as social trust and civic engagement. Following Williams (2006), this study focused on the outcomes of social capital instead of the social network itself.

Social capital can be delineated into bonding and bridging social capital (Putnam, 2000). Bonding social capital refers to deep and homogeneous connections and strong ties that generate the exchange of resources such as emotional support and trust. In contrast, bridging social capital describes wide and heterogeneous connections and weak ties that facilitate a sense of belonging to a large interconnected group, community engagement, and broader worldviews. Social capital is further categorized into offline and online bonding and bridging social capital because people not only form and keep social capital in real life, but also through the Internet (Williams, 2006).

As social capital is a multidimensional construct, this study also included the interpersonal and behavioral domains of social capital (Scheufele and Shah, 2000). The interpersonal domain refers to social or generalized trust in individuals in a society. Building upon imperfect information, social trust is a belief that unknown others do not intend to harm self (Putnam, 2000). The behavioral domain in this study involves civic participation. Civic engagement consists of personal and collective prosocial behavior that can benefit others and solve problems of the community, such as being a volunteer in nongovernmental organizations and fundraising for a charity (Valenzuela et al., 2009).

Eras of research on media use and social capital

Whether individuals' social capital is positively or negatively influenced by media use has been an important topic in the field of communication. The first era of research studied the relationship between mass media exposure (particularly television viewing) and social capital. Putnam (2000) argued that television serves as the driving force behind the reduction in social capital. Television viewing privatizes individuals' leisure time and thus restrains interpersonal communication and civic activities outside the home (Nie, 2001; Putnam, 2000). Previous studies on television exposure–social capital association demonstrated inconsistent results. Some studies found negative impacts of television viewing on generalized trust and civic engagement (Hooghe and Oser, 2015; Moy et al., 1999). Others showed no relationship between exposure to television and offline network capital (Hooghe and Oser, 2015; Vergeer and Pelzer, 2009). Indeed, the relations between television viewing, interpersonal trust, and civic engagement depend on the type of television program people watch rather than how much they watch (Shah, 1998).

Putnam (2000) posited that not only watching television but using the Internet is also the cause of the decrease in social interaction, interpersonal trust, and civic participation. However, contrary to exposure to television, previous research found a positive link between Internet use and social capital (Ellison et al., 2007; Hooghe and Oser, 2015) mainly because of its interactive nature (Valenzuela et al., 2009; Williams, 2006), particularly the social network sites. The second era of media use–social capital research concentrated on examining the effect of social media use on social capital. Different from the negative or no relation between television viewing and social capital, numerous empirical studies have indicated positive linkages between use of different social network sites and offline and online bonding and bridging social capital. Facebook use can cultivate social resources embedded in individuals' interpersonal relationships within their network (Ellison et al., 2014). The usage of other social media platforms (e.g. Twitter, Instagram) also generates bonding and bridging social capital (Hofer and Aubert, 2013; Phua et al., 2017). People can share and gain social and emotional resources without geographical constraints by using social media (Ng, 2020).

Little research has examined the linkage between use of conversational AI and social capital. A study found that people with a higher cognitive social capital (generalized trust and reciprocity) have a favorable perception of AI, but people with a higher structural social capital (high frequency of contact with others) are antagonistic toward AI (Inaba and Togawa, 2021). Still, not much is known whether conversational AI functions as a communicator (Guzman and Lewis, 2020) would facilitate or hinder social capital. While Inaba and Togawa (2021) proposed that different types of social capital could generate different attitudes toward AI use, this study explores whether conversational AI use would relate to an increase or decrease in social capital. The conversational AI use-to-social capital and social capital-to-conversational AI use linkages are discussed in the "Discussion" section.

This study would expand our understanding of the possibility of social capital formation by using conversational AI in the latest era. From mass media to social media, the nature of the media changes from unidirectional to interactive ones. The transformation is the traditional media people cannot communicate through to mediators (social media) individuals are able to communicate through. Individuals are unable to communicate with other individuals when watching television, but they can use social media platforms to interact with others (Valenzuela et al., 2009; Williams, 2006). Thus, people develop social capital through social media use, but reduce it through television exposure. From social media to communicative AI media, the nature of the media modifies from interaction with other people through the media to interaction directly with the media—mediators (social media) people communicate *through* to communicators (communicative AI media) people communicate *with* (Natale, 2021; Sundar, 2020). Human–human communication through the use of mediators (computer–mediated communication) can cultivate social capital. Is the use of communicators (human–conversational AI communication) positively or negatively associated with social capital?

Conversational AI use and social capital

It is possible that conversational AI use is related to decreases in social capital. According to the time displacement hypothesis (Nie, 2001; Putnam, 2000), individuals spend a considerable amount of their leisure time on television. They then sacrifice their spare time to interact and communicate with others for watching television. People sitting in front of the television have less time available for community and civic activities that could build social capital (Putnam, 1995, 2000). Following this logic, individuals may sacrifice their time to communicate with other individuals for communicating with conversational AI. They may not have enough time to initiate and form social capital through interpersonal interaction. Also, people watch television in the private life-sphere, usually at home, with limited communication with other people. The cultivation of a mean world syndrome that things happening outside private life are perceived as potential threats (Gerbner, 1998) could incur television viewers to refrain from social interaction (Hooghe and Oser, 2015). The cultivation effect may apply to the use of conversational AI that people use the devices privately without sufficient interaction with others. They may perceive the outside world as more dangerous than it actually is, thus further avoiding social capital formation.

It is probable, however, that conversational AI use is linked to increases in social capital. According to media equation theory (Nass and Moon, 2000; Reeves and Nass, 1996), people mindlessly deal with new media technologies similar to other real people, and treat media technologies as if they have their own purposes. It is because humans have not yet been evolved to differentiate between mediated and non-mediated experience. Thus, humans adopt social rules to communicate and interact with media technologies (Nass and Moon, 2000). The media technologies are perceived by humans as social actors when technologies diametrically exchange information with humans (Nass et al., 1994), although the human–human social scripts for human–human communication could be different from human–(AI) media social scripts for human–AI communication (Gambino et al., 2020). When it comes to conversational AI that functions as communicators, the communicators could also be interpreted by humans as actors (Guzman and Lewis, 2020). While television viewers are typically not active to communicate with other viewers through the television (Williams, 2006), conversational AI users can take an active role in interacting with conversational AI as the communicators, which are perceived by them as social actors (Ng, 2021).

Humans can communicate with human-like non-human social actors (e.g. conversational AI), but can interactions with conversational AI link to individuals' social interactions with other individuals and then construct social capital? The computers are social actors approach (Nass et al., 1994) explains humans' initial social reactions to and interactions with media technologies. The revised ethopoeia concept (Nass and Yen, 2010) posits that sophisticated media technologies incarnate more social cues and elicit cognitive heuristics. The mental shortcuts could direct humans to adopt identical social expectations and rules not only to initial interactions with media technologies, but also subsequent social interactions with humans. For instance, a study showed that the social processes existed for initial interactions with sophisticated media agents are applied to subsequent interactions with both humans and AI (Velez et al., 2019). Another study found that interactions between humans and artificial agents can influence human-to-human communication. People interacting with speaking robots tend to feel more comfortable talking to other people, and are more willing to participate in social engagement in conversations (Traeger et al., 2020). Because conversational AI can talk and display sophisticated social cues (Guzman, 2019), people's interactions with conversational AI could relate to an increase in social interactions with other people, as proposed by the revised ethopoeia concept (Nass and Yen, 2010). Accordingly, the social interactions can cultivate social capital, both offline and online.

Due to the exploratory nature of this study, the following research questions were raised:

RQ1. Is there a difference between users and non-users of conversational AI in (RQ1a) offline bonding social capital, (RQ1b) online bonding social capital, (RQ1c) offline bridging social capital, (RQ1d) online bridging social capital, (RQ1e) social trust, and (RQ1f) civic participation?

RQ2. Is there an association between intensity of conversational AI use and (RQ2a) offline bonding social capital, (RQ2b) online bonding social capital, (RQ2c) offline bridging social capital, (RQ2d) online bridging social capital, (RQ2e) social trust, and (RQ2f) civic participation?

RQ3. Is there an association between frequency of conversational AI use and (RQ3a) offline bonding social capital, (RQ3b) online bonding social capital, (RQ3c) offline bridging social capital, (RQ3d) online bridging social capital, (RQ3e) social trust, and (RQ3f) civic participation?

The context of Hong Kong

According to the Smarter Digital City project (Google & KPMG, 2020), about 60% of people in Hong Kong adopt virtual assistants and about 50% use chatbots. In general, about two-thirds of Hong Kong people reckon that AI helps to ameliorate Hong Kong society. Only 2% of them think AI is a threat to people in Hong Kong, demonstrating a favorable attitude toward AI (Google & KPMG, 2020). While no studies have examined the association between conversational AI use and social capital among Hong Kong people, previous research has found that Hong Kong people who use mobile phones and mobile social media to interact with their family members and friends are more likely to report having higher social capital (Chan, 2015; Chen and Li, 2017). People in Hong Kong interacting with other people through the use of mobile phones and mobile social media can facilitate the maintenance of social capital. This study explores whether Hong Kong people interacting directly with conversational AI in mobile phones and other devices could also be related to social capital formation.

A prior cross-country study showed that, although there is a between-country variation, social capital can be developed on social media in different countries (Huber et al., 2019). Thus, the media use–social capital association could be discussed across different countries to a certain extent, though no research has yet explored the conversational AI–social capital relationship across countries. The theoretical argument in this study should be compatible with the context of Hong Kong. Taken together, the context of Hong Kong should be able to offer a suitable condition to investigate the research questions in this study.

Method

Sample

Target participants were the general population aged above 18 in Hong Kong. The sample was recruited from the YouGov proprietary panel conducted in May and June 2021. The research institute YouGov claimed that it adopted an active sampling approach that broad quota was applied on gender, age, education and income level. Post-weighting on a broader range of age and gender was adjusted to ensure that participants were representative of the total online population. The survey can be conducted through any computing device, for example, mobile, tablet, personal computer (PC), and laptop. A total of 1022 participants were recruited. Participants read the informed consent statement and agreed to participate in this study. This study was approved by the Research Ethics Committee of the author's university.

Measures

Conversational AI users. Participants were asked, "Are you currently using any conversational AIs/intelligent virtual assistants, such as Apple Siri, Google Assistant/Home, Huawei Celia, and Amazon Alexa?" They answered "yes" (38.9%) or "no" (61.1%).

Intensity of conversational AI use. Facebook intensity scale (Ellison et al., 2007) was adapted and modified to measure conversational AI usage. Participants who were conversational AI users (38.9%) were asked to answer five questions on five-point Likert-type-scales ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). The items were slightly revised from "Facebook" to "conversational AIs." The questions were shown in random order. The total five items were averaged to generate a composite index, with higher scores indicating higher conversational AI intensity ($\alpha = .84$, $M = 3.16$, $SD = 0.74$).

Frequency of conversational AI use. Participants were asked, "In the past week, on average, approximately how many hours per day have you spent on conversational AIs?" ($M = 2.60$, $SD = 1.61$; $1 \leqslant 5$ minutes: 31.66%, 2 = about 5–10 minutes: 22.36%, 3 = about 10–30 minutes: 21.36%, 4 = about 30 minutes to 1 hour: 13.57%; $5\text{–}9 \geqslant 1$ hour: 11.05%).

Offline and online bonding and bridging social capital. Referring to the Internet social capital scale (Williams, 2006), a short version was developed to measure bonding and bridging social capital (Lin, 2019). This short version scale was adapted and modified to assess offline and online bonding and bridging social capital in this study. Participants rated their level of agreement ranging from 1 (*strongly disagree*) to 5 (*strongly agree*) with three statements on each measure. The questions were presented in random order.

A confirmatory factor analysis was performed on the 12 items. This four-component model demonstrated an excellent fit: $\chi^2(48) = 113.20, p < .001$, CFI = 0.98, RMSEA = 0.04, SRMR = 0.02. For each subscale, the three items were averaged to create a composite index, with higher scores reflecting higher offline bonding social capital ($\alpha = .69$, $M = 3.60$, $SD = 0.59$), online bonding social capital ($\alpha = .75$, $M = 3.08$, $SD = 0.76$), offline bridging social capital ($\alpha = .70$, $M = 3.56$, $SD = 0.56$), and online bridging social capital ($\alpha = .78$, $M = 3.38$, $SD = 0.70$).

Social trust. To measure the interpersonal domain of social capital (Scheufele and Shah, 2000), one statement from the faith in people scale (Rosenberg, 1956) was adapted to assess social trust ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). The statement was the following: "Generally speaking, I would say that people can be trusted" ($M = 3.31$, $SD = 0.77$).

Civic participation. To assess the behavioral domain of social capital (Scheufele and Shah, 2000), civic participation was measured using three response choices from 1 (*no, never*) to 2 (*yes, but not within the last 12 months*) to 3 (*yes, within the last 12 months*;

Table 1. Mean (*M*) and standard deviation (*SD*) of measures of social capital comparing conversational AI users and *non-users*.

	Conversational AI users	Conversational AI non-users	*t*	*p*	Cohen's *d*
	($n=398$)	($n=624$)			
	M (*SD*)	*M* (*SD*)			
Offline bonding social capital	3.69 (0.59)	3.54 (0.59)	3.95	<.001	0.25
Online bonding social capital	3.31 (0.72)	2.93 (0.75)	8.13	<.001	0.52
Offline bridging social capital	3.69 (0.53)	3.47 (0.56)	6.39	<.001	0.41
Online bridging social capital	3.58 (0.66)	3.25 (0.69)	7.70	<.001	0.49
Social trust	3.46 (0.79)	3.21 (0.74)	5.20	<.001	0.33
Civic participation	1.67 (0.57)	1.37 (0.46)	9.24	<.001	0.59

AI: artificial intelligence.
$df=1020$.

Valenzuela et al., 2009). The three items were averaged to create an index of civic participation, with higher scores indicating greater value ($\alpha=.74$, $M=1.48$, $SD=0.52$).

Covariates. Referring to the previous studies on intensity of media use and social capital (Ellison et al., 2007; Valenzuela et al., 2009), demographic factors served as the control variables, including gender (52.2% females), age ($M_{age}=44.09$, $SD_{age}=14.22$, $Mdn_{age}=45$, $Min\text{–}Max=18\text{–}81$), personal average monthly income ($M_{income}=7.60$, $SD_{income}=3.66$, $Mdn_{income}=7$, 7=HK$20,000–24,999, equivalent to US$2580–3220), and education ($M_{education}=4.47$, $SD_{education}=1.46$, $Mdn_{education}=5$, 5=University degree).

Measurement items, notes, and online tables are available online at https://osf.io/2cfbp/?view_only=a90745881c5b496aa01cf0b2baffb992.

Results

To answer RQ1 (whether there is a difference between users and non-users of conversational AI in each measure of social capital), independent *t*-tests were conducted (see Table 1). Results demonstrated that conversational AI users scored higher on all measures of social capital than non-users. Users of conversational AI were more likely to report having higher (RQ1a) offline bonding social capital, (RQ1b) online bonding social capital, (RQ1c) offline bridging social capital, (RQ1d) online bridging social capital, (RQ1e) social trust, and (RQ1f) civic participation than non-users of conversational AI. Based on Cohen's (1992) effect size index for small (*Cohen's* $d=0.20$), medium (*Cohen's* $d=0.50$), and large effect (*Cohen's* $d=0.80$) for independent *t*-test, the findings indicated medium effect sizes for civic participation (*Cohen's* $d=0.59$), online bonding social capital (*Cohen's* $d=0.52$), and online bridging social capital (*Cohen's* $d=0.49$). The effect sizes were close to medium for offline bridging social capital (*Cohen's* $d=0.41$), small-to-medium for social trust (*Cohen's* $d=0.33$), and small for offline bonding social capital (*Cohen's* $d=0.25$).

To answer RQ2 and RQ3 (whether there is an association between intensity and frequency of conversational AI use and each measure of social capital respectively), six regressions predicting offline bonding social capital, online bonding social capital, offline bridging social capital, online bridging social capital, social trust, and civic participation were performed, respectively, for participants who were users of conversational AI ($n = 398$). Demographic factors (Model 1: gender, age, personal income, and education level), intensity (Model 2a) and frequency (Model 2b) of conversational AI use served as the predictors to associate with the six measures of social capital.

Online Appendix Table 1 shows that the four demographic variables in Model 1 explained 4% of the variance of offline bonding social capital. Younger participants and participants with a higher personal income reported higher offline bonding social capital. Adding intensity of conversational AI use in Model 2a improved the prediction accounting for 12.8% of the variance, *Adjusted* R^2 *change* = .09, $p < .001$. The results showed that conversational AI intensity was positively associated with offline bonding social capital, $\beta = .31$, $p < .001$ (RQ2a). Entering frequency of conversational AI use in Model 2b did not improve the prediction. It explained 3.82% of the variance, *Adjusted* R^2 *change* = –.002, $p = .57$. Frequency of conversational AI use was not related to offline bonding social capital, $\beta = .03$, $p = .57$ (RQ3a).

The control variables in Model 1 accounted for 3.85% of the variance of online bonding social capital (see Online Appendix Table 1). Male, younger, and participants with a higher personal income had higher online bonding social capital. Including intensity and frequency of conversational AI use in Model 2a and Model 2b significantly enhanced the prediction that explained 21.45% and 10.04% of the variance respectively, *Adjusted* R^2 *change* = .18, $p < .001$ for intensity and *Adjusted* R^2 *change* = .06, $p < .001$ for frequency. Personal income no longer predicted online bonding social capital in Models 2a and 2b. Conversational AI intensity ($\beta = .43$, $p < .001$; RQ2b) and frequency ($\beta = .26$, $p < .001$; RQ3b) positively predicted online bonding social capital.

Online Appendix Table 2 displays that the four demographic variables in Model 1 explained 3.71% of the variance of offline bridging social capital. Similar to offline bonding social capital, younger users and users with a higher personal income reported higher offline bridging social capital. Entering intensity and frequency of conversational AI use improved the prediction accounting for 14.03% and 4.73% of the variance respectively, *Adjusted* R^2 *change* = .10, $p < .001$ for intensity and *Adjusted* R^2 *change* = .01, $p = .026$ for frequency. Personal income was no longer a significant predictor in Model 2a. The findings indicated that intensity ($\beta = .33$, $p < .001$; RQ2c) and frequency ($\beta = .11$, $p = .026$; RQ3c) of conversational AI use positively predicted offline bridging social capital.

The control variables in Model 1 explained 4.95% of the variance of online bridging social capital (see Online Appendix Table 2). Similar to offline bonding and bridging social capital, younger users and users with a higher personal income owned higher online bridging social capital. Including the conversational AI intensity in Model 2a and frequency in Model 2b significantly increased the prediction explaining 22.17% and 9.66% of the variance respectively, *Adjusted* R^2 *change* = .17, $p < .001$ for intensity and *Adjusted* R^2 *change* = .05, $p < .001$ for frequency. Personal income was again no longer a significant predictor, but male participants tended to have more online bridging social capital in Model 2a. The findings revealed that conversational AI usage intensity ($\beta = .42$, $p < .001$; RQ2d) and frequency ($\beta = .23$, $p < .001$; RQ3d) were positively correlated with online bridging social capital.

Online Appendix Table 3 displays that Model 1 accounted for 1.8% of the variance of social trust. Similarly, younger users and users with a higher personal income showed higher social trust. Entering intensity and frequency of conversational AI use in Models 2a and 2b increased the prediction accounting for 9.65% and 3.62% of the variance respectively, *Adjusted* R^2 *change* $= .08$, $p < .001$ for intensity and *Adjusted* R^2 *change* $= .02$, $p = .005$ for frequency. Personal income no longer predicted social trust in Models 2a and 2b. Intensity ($\beta = .29$, $p < .001$; RQ2e) and frequency ($\beta = .15$, $p = .005$; RQ3e) of conversational AI use was positively related to social trust.

The demographic variables in Model 1 explained 3.2% of the variance of civic participation (see Online Appendix Table 3). Participants with a higher personal income and a higher education level were more likely to engage in civic participation. Adding the conversational AI intensity in Model 2a and frequency in Model 2b enhanced the prediction explaining 7.29% and 11.72% of the variance, *Adjusted* R^2 *change* $= .04$, $p < .001$ for intensity and *Adjusted* R^2 *change* $= .09$, $p < .001$ for frequency. Again, personal income no longer predicted civic participation in Models 2a and 2b. Conversational AI usage intensity ($\beta = .21$, $p < .001$; RQ2f) and frequency ($\beta = .30$, $p < .001$; RQ3f) positively predicted civic participation.

Based on Cohen's (1992) effect size index for small ($f^2 = 0.02$), medium ($f^2 = 0.15$), and large effect ($f^2 = 0.35$) for multiple regression, regarding intensity of conversational AI use, the results demonstrated medium-to-large effect sizes for online bridging social capital ($f^2 = 0.29$) and online bonding social capital ($f^2 = 0.27$), and medium effect sizes for offline bridging social capital ($f^2 = 0.16$) and offline bonding social capital ($f^2 = 0.15$). The effect sizes were close to medium for social trust ($f^2 = 0.11$) and small-to-medium for civic participation ($f^2 = 0.08$). Regarding frequency of conversational AI use, the findings revealed medium effect sizes for civic participation ($f^2 = 0.15$), online bonding social capital ($f^2 = 0.13$), and online bridging social capital ($f^2 = 0.12$), and small effect sizes for offline bridging social capital ($f^2 = 0.06$), offline bonding social capital ($f^2 = 0.05$), and social trust ($f^2 = 0.05$).

Discussion

The purpose of this study was to explore the associations between the use of conversational AI and measures of social capital, including offline and online bonding and bridging social capital, as well as the interpersonal domain (i.e. social trust) and behavioral domain (i.e. civic participation) of social capital. Although causality cannot be established, by utilizing a territory-wide survey of an online representative sample in Hong Kong, the results showed consistent evidence that the positive conversational AI use–social capital associations occurred. Conversational AI users in Hong Kong reported having more (RQ1a) offline bonding social capital, (RQ1b) online bonding social capital, (RQ1c) offline bridging social capital, (RQ1d) online bridging social capital, (RQ1e) social trust, and (RQ1f) civic participation than non-users. For the conversational AI users, (RQ2a–f) intensity and (RQ3b–f) frequency of conversational AI use positively predicted the six measures of social capital after taking into consideration the demographic variables (gender, age, personal income, and education level), except that (RQ3a) frequency was not related to offline bonding social capital.

This study could provide contributions to the literature on media use and social capital. Previous studies have demonstrated a negative or no relationship between traditional media use (television viewing) and social capital (Hooghe and Oser, 2015; Moy et al., 1999; Vergeer and Pelzer, 2009), and a positive association between social media use and social capital (Ellison et al., 2007; Valenzuela et al., 2009). Research on the use of traditional and social media and associated social capital formation has been well-studied. Little is known, however, about the relationship between use of communicative AI media and social capital. This study is among the first to empirically show that, as predicted by the revised ethopoeia concept (Nass and Yen, 2010), conversational AI use is positively related to social capital outcomes. In this era of media convergence, individuals not only communicate with other individuals through social media, but also communicate directly with communicative AI media (Guzman and Lewis, 2020; Natale, 2021; Sundar, 2020). The interactive nature of new media (both social media and communicative AI media) can relate to the development and formation of social capital.

The time displacement hypothesis (Nie, 2001; Putnam, 2000) has mainly been considered to illustrate the (negative) relationship between media use and social capital production. Contrary to the time displacement approach that people using media technologies lack time to communicate with other people, this study showed that social capital could be positively associated with conversational AI use. Individuals sitting in front of the television may have to sacrifice their spare time to interact with others, but spending time using new media could enhance their chance of forming connections with other individuals. This study found that, instead of insufficient interaction with other people because of conversational AI use, spending time using the devices could relate to social capital formation.

By adopting the computers are social actors approach (Nass et al., 1994) and the revised ethopoeia concept (Nass and Yen, 2010) as the possible theoretical frameworks, the findings of the present study implied that people in Hong Kong could utilize social rules to interact with both conversational AI as the human-like non-human social actors and other people. The social interactions with conversational AI and other people are intercorrelated. Consistent with the previous studies (Traeger et al., 2020; Velez et al., 2019), the social processes occurred for the interactions between humans and sophisticated media technologies (e.g. conversational AI) are linked to human–human interactions. It is possible that people talking to conversational AI appear comfortable communicating with other people (Traeger et al., 2020). Thus, although the causal relationship cannot be tested in this correlational study, conversational AI users tend to be more likely to report having higher online and offline social capital through social interactions than non-users.

The results of this study indicated that the use of conversational AI was positively associated with all the four measures in the Internet social capital scales (i.e. offline and online bonding and bridging; Williams, 2006) and the interpersonal and behavioral measures of social capital (i.e. social trust and civic participation; Scheufele and Shah, 2000), except that frequency of use was not correlated with offline bonding social capital. Thus, conversational AI use should play an important role in cultivating various forms of social capital. Specifically, the findings showed larger effect sizes for online bonding and bridging social capital than offline bonding and bridging social capital. The effects for the conversational AI use–social capital formation association are stronger online than offline. A possible explanation is the source interactivity that blurs the line between computer-mediated communication and human–machine communication (Sundar, 2012). It refers to the capability of new media users to serve as sources of interaction. In the era of interactive media (social media and communicative AI media), media users smoothly and continuously communicate and interact with other individuals and the interfaces. They adopt the interface features to execute interactions with individual, group, and mass communications as well as the media directly (Sundar, 2020). Because the distinctions between human–human interaction through the media and human–conversational AI interaction have blurred, it is thus reasonable to observe a larger effect size for the conversational AI use–online social capital relationship than the conversational AI use–offline social capital relationship. New media users seamlessly interact with both other new media users and conversational AI, thereby making it possible for conversational AI users to report having higher social capital online than offline.

A main theoretical contribution is that this study identified that the association between conversational AI use and social capital is positive. Some may argue that the use of conversational AI is not prevalent and its influence may not be salient. However, the data of this representative sample showed that about 40% of Hong Kong citizens were conversational AI users and the conversational AI use–social capital relationship is significant. The findings of this research can provide preliminary empirical evidence for future studies to explore the underlying mechanisms that can explain the positive linkage. One potential explanation is that using conversational AI can enhance individuals' comfortability of communication (feeling comfortable talking to other people), and can thus cultivate social capital through social interactions (Traeger et al., 2020). Future research could explore other social skills as the mediators.

It is noted that the findings generally showed medium-to-large and medium effect sizes for the social capital measures regarding intensity of conversational AI use, but medium and small effect sizes regarding frequency of use. Emotional attachment to and experience and engagement in conversational AI use can explain the social capital formation more than simply time spending on it. The results implied that future research could explore the roles that various emotional factors and user interface experience and engagement can play in explaining the positive conversational AI use–social capital linkage.

This study focused on investigating the conversation feature of conversational AI use and associated social capital. However, people use conversational AI to satisfy not only their need for social interaction and social presence (Cheng and Jiang, 2020; McLean and Osei-Frimpong, 2019), but also various gratifications generated from the usage of conversational AI, including hedonic, functional, informational, and diversion gratifications. A previous study found large effect sizes for hedonic, functional, and social gratifications (Cheng and Jiang, 2020). The strengths for the conversational AI usage–social capital formation association could be different for different gratifications. People adopt conversational AI to gain hedonic benefits (hedonic gratification: killing time, feeling entertained, and seeking fun), enhance efficiency and productivity in performing their work (functional gratification: improving preciseness and reducing the time to resolve problems), and gratify their need to escape from reality (diversion gratification: getting away from annoying people and issues; Cheng and Jiang, 2020; Lee and Cho, 2020; McLean and Osei-Frimpong, 2019). These gratifications of conversational AI use should be unrelated (or negatively related) to social capital formation. However, if people fulfill their need to obtain news and information and gain new knowledge by adopting conversational AI (Lee and Cho, 2020), this informational gratification could be associated with an enhancement in social capital. It is because online news consumption positively predicts social capital (Gil De Zúñiga et al., 2012). Future studies could examine the relationships between various gratifications of conversational AI use and social capital.

To put it simply, social capital refers to connections and trust with family members, friends, and strangers. In the case that conversational AI use can increase individuals' connections and interactions with other people (social capital), probably because conversational AI adopts natural language characterized by human-like features (e.g. voice) to interact with people in real-time, people could perceive conversational AI as similar to some characteristics of human beings (i.e. perceived anthropomorphism) and feel the presence (i.e. perceived social presence) of the conversational AI (Fernandes and Oliveira, 2021; Pitardi and Marriott, 2021; Yen and Chiang, 2021). Consequently, people talking to conversational AI feel comfortable connecting with other individuals (Traeger et al., 2020). Future studies could examine whether perceived anthropomorphism and social presence would mediate the conversational AI use–social capital relationship.

However, it can also be the case that people who have more social capital would be more likely to use conversational AI. By adopting the uses and gratifications approach (Katz et al., 1973; Rosengren, 1974), previous studies found that social gratification is one of the motivations driving people to use conversational AI (Cheng and Jiang, 2020; Choi and Drumwright, 2021). It is possible that people are motivated to use conversational AI because human beings are social animals who need to use media technologies to gratify the need to connect with others (Ng, 2020). Conversational AI can be perceived as people's friends (Choi and Drumwright, 2021; Schweitzer et al., 2019), and its interactive feature affords people to satisfy their social gratification (Choi and Drumwright, 2021; Sundar and Limperos, 2013). Thus, people who are motivated to connect with others could be more likely to use conversational AI to gratify their social needs. This study could trigger future longitudinal studies to test whether conversational AI use causes social capital formation or social capital fosters conversational AI use.

This study could offer some practical implications. First, policymakers are interested in how the concept of smart city can benefit citizens in a society. Conversational AI is one of the applications of AI technologies. The findings of this study showed that conversational AI use is related to social capital formation, which is another concept that attracts policymakers. The results serve as empirical support for AI projects in the public sector as a reference. Second, AI developers argue that people can apply AI for social good to improve people's lives. This study can be an empirical finding to support the idea of using AI for social good. Conversational AI can help people form connections with other people and could make their lives better. Third, mental health professionals could make use of the findings of this study to explore the possibility of supplementing social support, as social support is linked to better mental health and better response to trauma.

This study had some potential limitations. The present research was a correlational study. The findings cannot establish the causal effect of conversational AI use on social capital. Future research could study how social capital formation may change over time due to conversational AI use by conducting a longitudinal study. Also, this study used a territory-wide survey of an online representative sample of the Hong Kong population. Future studies could examine the associations in other cultures, regions, and countries to replicate the findings.

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ORCID iD

Yu-Leung Ng https://orcid.org/0000-0002-7140-1616

Supplemental material

Supplemental material for this article is available online.

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Author biography

Yu-Leung Ng is a research assistant professor at the Department of Journalism, Hong Kong Baptist University. His research interests include media psychology, psychological impacts of new media technologies, human-AI interaction, and AI-mediated communication (Email: yuleungng@hkbu.edu.hk).