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Digital assistants: Inequalities and social context of access, use, and perceptual understanding

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ABSTRACT

This study focuses on digital divide in the context of access, use, and perceptual understanding of digital assistants. We pay particular attention to inequalities of perceptual outcomes that may be triggered by the first-(access) and second-level (use) divides. We extend this insight to the level of perceptual understanding and investigate how the understanding of various personalized AI-related applications—as manifested via the consumption of functional and informational features of digital assistants—vary depending on access and use. Our analyses of two U.S. national surveys reveal the first and second divides, such that those in higher status (higher income) enjoy higher access and use. Then, we also find related perceptual gaps along the line of socio-demographics, as the pattern was evident for education in interaction with other demographic backgrounds. That is, there were varying degrees of the understanding of algorithmic misjudgment, bias in recommended content, or data surveillance, while users with lower social status tended to easily overlook those risks for their excitement and convenience of AI-enabled devices. We argue that inequalities operate in terms of material (access/use) as well as socio-cultural (perceptual understanding) bases, suggesting how digital opportunities instigated by digital assistants may not be built on levelled grounds and continue to consolidate and reproduce existing inequalities in recursive ways.

1. Introduction

Unconditional welcoming of new technologies, such as digital assistants, may be inadequate, as many have pointed out legitimate reasons for skepticism about artificial intelligence (AI)-enabled applications that come to light via the access and use of digital devices (Cheney-Lippold, 2018; Noble, 2018; Park & Jones-Jang, 2022; Seaver, 2017). First, new technologies and inventions arise out of social context. As seen in digital inequalities on the Internet, socially benefited demographics enjoy opportunities for easier access and use. Second, the potential of technologies comes to a full realization at the interface of consumption, as the condition under which a new AI-enabled technology is accessed, put to a use, and understood is likely to determine its future affordance (DiMaggio et al., 2001; Neuman, 2016). There is evidence and a solid theoretical foundation (Van Deursen & Van Dijk, 2014; Van Dijk, 2020) attesting to the

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resilience of social inequalities in various forms of digital technologies. That is, those in higher social positions enjoy advanced access, use and perceptual skill sets to take better advantage of material bases, which result in enhanced accumulation of capital resources in life outcomes. Addressing these, we examine the reception of digital assistants, such as Google Home, Amazon Alexa, or Echo, from the standpoint of digital divide. We are particularly interested in the extent to which one's social position creates disparities in terms of access, use, and perceptual understanding of AI-based functions and information in their reception.

Digital assistants as the object of our inquiry symbolize the complexity of AI, with devices such as Google Home or Amazon Alexa becoming one of the most accessible forms of functional AIs at home—or simply put, automated personal helper ubiquitously present in our home. AI has become de facto elements in social media, IoTs (Internet of Things), or even domestic robots such as Amazon Astro, with their core features enabled by AI—namely, from an email spam filter to Google Translator, product recommenders, autocomplete systems, voice recognition, and so on. This multiplicity of AI-applications embedded in digital platforms makes inquiries of AI complicated, as disparate epistemological backgrounds among software engineers, business communities, or publics make operational definitions of AI hardly agreeable (Seaver, 2017). Subsequently, debates on AI diverge into different focuses on technical opaqueness, functional trap (Seaver, 2019), or data manipulation/discrimination (Cheney-Lippold, 2018; Gillespie, 2016), heralding the complexity as to how the public comes to understand the problems associated with AI in its algorithmic misjudgment and bias in recommended content, or surreptitious data collection.

In this study, we operationalize personalized AI-application in two aspects: (1) function (what it does operationally) (Study 1) and (2) information (what it recommends) (Study 2) (Van Deursen & Van Dijk, 2010), analyzing U.S. samples of two years (2017, 2019) with respective emphasis on the perceptual understanding of people's access and use of digital assistants. Foremost, our concern is on varying socio-demographic backgrounds predicting a critical reception of digital assistants, while users easily overlook potential risks over the novelty, fun, or ease of AI-enabled function and information (van der Zeeuw et al., 2020). The 'black-box' complexity of AI—built 'under-the-hood' in consumer products—renders the costs invisible from the part of users (Hargittai et al., 2020), the problem possibly exacerbated by relative disadvantages of lack of access available among marginalized people. That is, certain categories of populations miss out opportunities to evaluate, and thus participate, critically in its digital offerings that come with hidden costs of bias and surveillance, but only engaged in surface-level uptake of AI.

Bourdieu's work (1984) directs our thesis to a sociological insight in that the reproduction of inequalities is a reflection of socially-rooted sets of practices uniquely accessible for people with distinctive socio-economic resources. Here one might characterize our concern as a type of 'Matthew effect'—or widely known as a recursive feedback loop that helps cumulate preexisting resources for those already in power (Neuman et al., 2011). We situate this recursive pattern of socio-reproduction of inequality within the broad context of digital 'last mile'—the end point of consumption where an individual's exposure to AI-enabled applications actually occurs. Recent studies (Gran et al., 2020; Klawitter & Hargittai, 2018; Lutz, 2019) in fact began to expand this insight to examine users' ability to figure out the operation of algorithm and its influences on their interaction with AI-enabled devices. Gran et al. (2020) in particular investigated algorithm awareness (personalized newsfeeds) in Norway and found its relationships to key demographics, as they termed it as the emergence of a new digital divide. Thus, recursive trap of socio-demographics in which one's resources 'hook' her/his digital standings poses enduring challenges, as this study calls for an investigation regarding reformulation of inequalities, measured in this study as access/use/perceptual understanding, as manifested via the consumption of digital assistants.

2. Digital inequality of digital assistants on perceptual understanding

Notwithstanding a reason to celebrate personalized AI applications in such areas as medicine, in which human decisions can be better off with the benefit of data-driven recommendations, the reason for concern seems also graving, given that AI applications, serving as a de facto entry point of digital platforms as in digital assistants, pose risks of surveillance, loss of autonomous control, and manipulation. As Anderson and Rainie (2018) aptly capsulated,

> decision-making on key aspects of digital life is automatically ceded to code-driven,
>
> "black box" tools. People…do not learn the context about how the tools work. . .
>
> sacrifice independence, privacy and power over choice; they have no control over these
>
> processes. (p.3).

Hereby, the first- and second-level divides bring a fruitful line of discussion to user end point, by suggesting that there might be inequalities emergent out of digital consumption in which members of diverse social groups in their access and use of AI-application understand technological risk and benefits on an unequal term.

Van Deursen and Helsper (2015) originally conceived the emergence of social gap based on Internet diffusion, given that differentiated use and access under certain socio-demographic conditions would be more optimal than others in translating their access and use to positive outcomes. Importantly, their idea substantiates the well-known premise of the first- and second-level digital divide (DiMaggio et al., 2001; Hargittai, 2002; Van Dijk, 2020; Van Laar et al., 2020, for a comprehensive review). These scholars rightly suggested that crucial differences between 'haves' and 'have-nots' are not solely built upon the unequal access to infrastructural material bases (i.e., having a hardware ownership of a device/technology), but also upon uses and/or skills on superstructure level (i.e., having a mastery of that device in actual use) that might be unevenly distributed.

Drawing from this, what we propose is that there can be a recursive feedback loop—that is, yet another critical layer of technology-related inequalities that are further stretching existing disparities on top of the first- (access) and the second-level (use) divides. This is a useful account of technological diffusion, such as AI-based assistants, and consequences on how it is understood at the outset of new innovative artefacts (Van Dijk, 2020). Instead of assuming that the advantage of having more access and achieving a higher level of use may be automatic and uniform, situating the recursive loop between the first and second level helps us see how inequalities can emerge on each level of the divide both respectively and jointly, with those inequalities embedded in different layers of socio-technological structure linked to each other.

Figure 1 captures this insight—a recursive trap in which one-level of divide, based on socio-demographic differences, can be easily transferred to another level of divide, perpetuating existing offline inequalities into other technology-related life experiences and culture, as in our case of perceptual understandings (Beer, 2017; Seaver, 2017). Each level of divide witnesses the reproductive power of socio-demographics in explaining the reception of AI-based assistants, enabling us to consider which population will be most vulnerable in an early stage of adoption. Then, as consequences of unequal use and access, we can also understand how perceptual gaps emerge between those 'haves' and 'have-nots' as members of privileged social groups are better equipped to perceive risks and problems associated with new technologies, rather than being unconditionally receptive (Klawitter & Hargittai, 2018; Marvin, 1988). Collectively, this allows us to answer a question regarding precise characteristics of the public reception of a new technology, as it can diverge continuously along with class, gender, race, and other offline axes of inequality.

Examining technology-related understanding as a dependent variable needs to be warranted, as people's use of technological products is also their acceptance of social contexts in which the new technology is put into a material form. Previous studies on sociomateriality (Leonardi, 2013) establish that a person's full experience with technologies may itself be socially constructed; henceforth, how a technology is developed into a social practice reflects people's perceptual experience with it. The insight resonates with digital inequality studies, in that motivational access to technologies is regarded as growing both of a social and of psychological nature, thus varied unique to respective environments (Van Dijk, 2020). Although Van Dijk's works (2020; Van Deursen & Van Dijk, 2010), for instance, place tech-related perception in the tier of motivational access before material access (thus, one is socially-culturally motivated for access), the lesson from those studies is that the way in which access and use of a technology come to a shape with particular effects is the socially endogenous process. Instead of placing access as a departure point of cause-effect, what we modify in our conceptualization of a recursive feedback loop is that how one comes to understand new technologies, through the lens of certain perceptual orientations, can be consequential, not only motivational, in a bi-directional recursive chain. To us, this is the fundamental point, as our premise is not to regard access/use as a single determinant, but as technological influencers or mediating agents through which the unequal societal conditions get channeled and reinforced in the formation of perceptual understanding.

Sociological literature has long addressed how understanding, as well as values and evaluation, regarding artefacts, technologies, or environments, are being shaped according to one's status. Socio-cultural valuation, according to Lamont (2012), is a legitimization process in which values of particular goods, entities, and related social practices are recognized. Importantly, Boltanski and Thévenot (1999) saw this to be socially contextual and interactional. Though their work did not directly address this as a hierarchical process, they provide us with an insight into how one's value can be structurally grounded in interaction with others in similar social positions, and thus, hierarchical. That is, the accumulation of capacity to engage in critical evaluation and appreciation is unevenly distributed. We recognize the Weberian perspective (Ragnedda, 2017), while rejecting that the formulation of status is based solely on an economic form of capital.

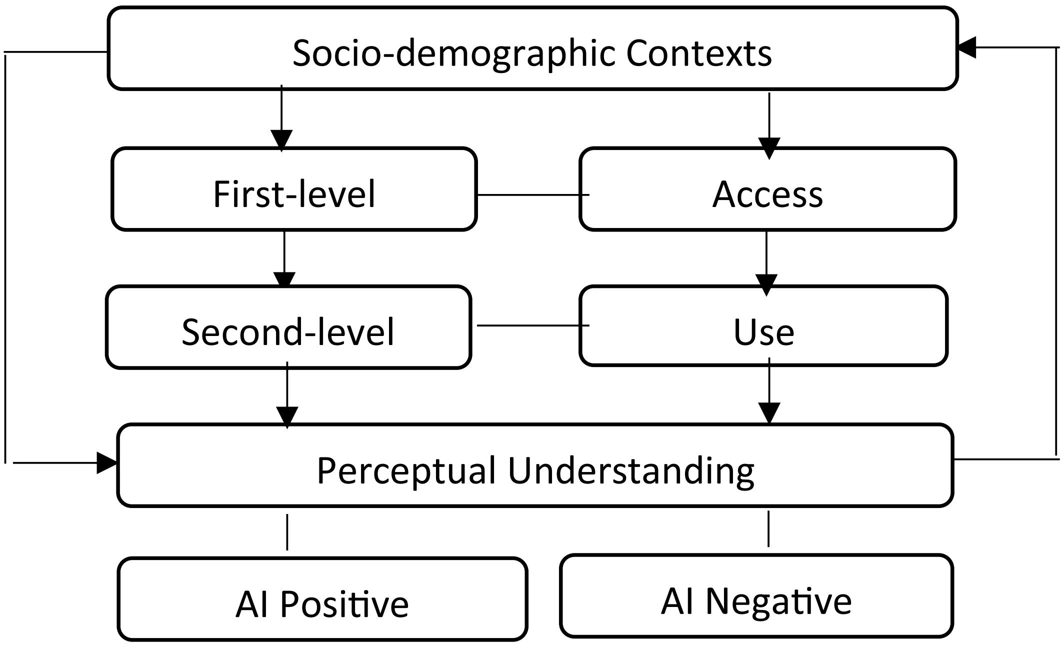

Fig. 1. Recursive trap in respective divide

But to us, Bourdieu's premise (1984) provides even a deeper line of reasoning as to why the perceptual ability for critical understanding has the major stake in reproducing one's position. For Bourdieu, this is a capital—and a form of power and social structure which determines one's patterns of evaluation and understanding, imposing criteria of engagement (also Lamont, 2012). Here the ability for critical understanding is not an embodied capital in absolute terms; it always depends on one's social position. In this sense, understanding or beliefs about a new technology can be regarded as the consequence of explicit discourses unique to one's societal positions (declarative), rather than unconscious and tacit (non-declarative) cultural dispositions (Lizardo, 2017)—that is, sort of everyday disposition and grammar possessed of the capacity for criticism (Boltanski & Thévenot, 1999). The reason why critical algorithm studies (Airoldi, 2021; Beer, 2017) regard algorithms—AI applications in general—as signifying power is that they exert control beyond immediate impact via material presence or technical-mechanism (which turned out to be problematic-biased against women, Noble, 2018). Algorithmic power arises from, not only how it is built internally to treat people, but also how people's choices are made in its use and perceptions, deploying boundaries in their daily reoccurrence where certain populations establish autonomy against algorithmic influences, while others cannot.

3. Hypotheses and research questions

The collective insights above lend credence to the importance of actual consumption on the basis of perceptual understanding, as well as access and use, which can perpetuate inequalities. The perspectives of the third-level and second-level divides share a fundamental point of view that increased access alone will not remedy unequal distribution of digital resources (DiMaggio et al., 2001; Van Dijk, 2020). Rather, leveling the field will be complex and multi-leveled, given that a certain form of a belief system deeply ingrained in a social group can be an enduring basis of inequalities. Understanding the dynamics of perceptual formation related to certain ways of beliefs about technologies will provide critical insights into sociocultural contexts in which technologies, such as AI-personal applications, are received unevenly among different socio-demographic groups, and help determine how people benefit from the same technology differently.

We use the term 'perceptual' to differentiate from 'factual' knowledge; that is, one's lay understandings of technologies are oftentimes not about factual features or principles of that technology. To us, this is a useful distinction to recognize everyday dispositions (Lizardo, 2017) through which ordinary users engage in evaluative judgement about the opaque nature of AI-based technologies. Even more critically, such systematic gaps can consolidate or exacerbate existing inequalities, precisely because they extend preexisting status differences to another social position (Airoldi, 2021), in which members of certain groups cannot critically evaluate—therefore, they remain vulnerable to the risk of surveillance or the difficulty of maintaining autonomous control, while benefiting from afforded advantages, such as ease of convenience or even fun associated with automated functions of technologies (Cheney-Lippold, 2018; Seaver, 2019). Ultimately, the links between people's understanding and their decision about AI-related consumption can turn out to be crucial, perpetuating a recursive pattern of inequality.

The tenet of our argument is that the perceptual understanding is particularly important in an early stage of technological diffusion, because the 'black box' nature of AI in its accessible form of applications such as digital assistants completely blinds the public about inner workings of algorithm. A qualitative interview project, however, found that even this opaqueness of AI-algorithms was found to be varying by one's experience with a particular platform (Gruber et al., 2021), indicating a possibly critical link between AI use-experience and understanding. Scholars (e.g. Christin, 2020) also began to point out that algorithms are experience technologies, thus, the understanding of their complex natures occurs through the actual use that is continuously influenced by social disparities. Airoldi (2021), by examining user selection of music tastes on YouTube, also characterized this as techno-social feedback loops on culture—similar to the Matthew effect in that algorithms reproduce preexisting (music) taste distinctions that too are much the product of social backgrounds (Bourdieu, 1984; Neuman et al., 2011). This line of thinking affords us to infer that actual consumption experiences, in a specific case of digital assistants, might be also much contingent upon those socioeconomic characteristics shaping one's understanding about the acceptance of AI-based assistants as well as its access and use.

Thus, examining socio-demographic variations regarding the reception of AI on those three-levels, we consider two disparate understandings. The first is the general support for AI-based assistants or its benefit that is celebrated for affording more power than human intelligence (AI-positive). The second is a negative or critical acceptance, measured by the perceived level of risk and hidden complexities (AI-negative), as they may pose a threat to the control over personal data in the use of digital assistants (Gandy & Nemorin, 2019; Park, 2021). On each level of access, use, and perceptional understanding, we hypothesize that preexisting inequalities, based on socio-demographics such as income, education, gender, age, and race, will be reinforced.

The proposition is that social environments prompt members of the same socio-demographic groups to think in common, act alike, and possess AI-related material resources in a similar fashion. This tendency will be accelerated by homogeneous social networks providing similar resources and frames of reference to people (Cotter & Reisdorf, 2020). We do not have specific reasoning—as Bourdieu (1984) specified in his original conception—tied to the process of one's socialization through family backgrounds. Rather, our proposition is more general: digital assistant access and use can operate like a form of cultural capital that reproduces advantages among those in higher status. That is, the stratified reception of AI-based assistants as a new technology can be instigated by everyday social discourse about AI in general—with their implicitly-shared experiences influencing particular choices about how much the technology should be integrated in everyday lives (Beer, 2017). Accordingly, we suggest the followings:

> H1: Sociodemographic status such as income (wealth), education (high), gender (men), age (younger), and race (white) will be positively related to levels of access (H1a) and use (H1b).

Bourdieu in his *Distinction* (1984) used income and education as a proxy for class, which provides a central basis for accumulating cultural tastes to appreciate high arts. We suspect that this is also the case for the process in which one begins to understand digital assistants and their AIs. Thus, although we are interested in influences of all socio-demographics, we expect that inequalities on the level of perceptual understanding will manifest particularly via income and education. Both income and education have been one of the most consistent status predictors for digital technology adoption. Those with lower income may not afford to develop a balanced viewpoint, remain unable to perceive related risks, and thus, cannot critically assess information automated from AI-based applications. Similarly, people with low education might forge only one scientific belief over another, have difficulties evaluating their potential vulnerability, and consequently, may be uncritically cheerful about technological wonder. In this case, the key investigation will be on the extent to which those with marginalized socio-demographic backgrounds are more receptive and less perceptive of AI risk, helping us answer how digital assistants in their various AI forms will be accepted in different socio contexts.

H2: Those with higher sociodemographic status, especially in terms of income and education, will have a higher level of critical understanding, as opposed to the general support, concerning AI-based digital assistants.

On the other hand, by controlling for socio-demographic variables, it is possible to test whether or not divergent understandings emerging out of AI are shaped systematically by basic access and its use. Previous digital divide literature well-established that a higher level of Internet access (the first-level divide) was connected to higher levels of use and skill (the second-level divide) (Hargittai, 2002; Van Deursen & Van Dijk, 2014). Thus, a link between the first- and second-levels in the case of AI-based assistants is warranted. However, we do not know precisely how that link, in transferring the first-level advantage to another, will eventually influence the perceptual understanding in terms of painting positive and negative viewpoints.

RQ1: How will the first- and second-level divides relate to the difference in perceptual understanding, controlling for socio-demographics?

Finally, in accounting for socio-demographic variations, we consider intersectionality—the interactive effects of socio-demographics in jointly reinforcing their respective influences (Choo & Ferree, 2010). The idea is that social life is too complex with multiple causal factors to be reduced into fixed categories of influence separated from one another. Particularly, we expect that the educational gap—jointly with other variables such as income, gender, age, and race—will widen even more on the perceptual ground, because the accumulation of wisdom based on education is likely to accelerate in other supportive environments, such as having higher income and better resources, being younger and being in a position to be surrounded by peers possessing tech 'know-how,' and being members of non-marginalized social status in terms of race and gender. Nevertheless, there is also a large body of counter-evidence that shows that a younger generation is not necessarily tech savvy (Hargittai, 2010; Livingston & Helsper, 2007) a certain marginalized group like African Americans was in fact a step ahead as seen in smartphone penetration (Smith, 2013); and the findings regarding gender difference have been mixed with regard to technology-related perceptions (Weiser, 2000). Thus, we have mixed clues on how education, in conjunction with other axis of unequal social conditions, will produce gap in their perceptual understanding.

RQ2: In accounting for the difference in perceptual understanding, how will the level of education interact with other socio-demographic variables?

4. Overview: study 1 and study 2

We test the above predictions using two cross-sectional surveys utilizing representative samples of the U.S. population. In each study, we examine hypothesized relationships of socio-demographics first with access (H1a) and use (H1b), and then with understanding (H2). Then, we investigate possible relationships between the different levels of divide, controlling for socio-demographic variables (RQ1). Finally, we explore the interactions between education and other socio-demographics with respect to AI-related perceptual understanding (RQ2), comparing the results from two samples. Defining AI is a complex one touching external (device-function) and internal (data-application) features, which also vary depending on how fully particular devices are AI-dependent. AI is an intelligent decision-making technology, while digital assistants such as Google Home or Amazon Echo are automated decision-makers built with AI inside applications. Accordingly, we examine (1) functional and (2) informational features of digital assistants, respectively in Study 1 and 2. [1]

4.1. Study 1: data and measures

We reanalyzed the Pew data collected in May 2017 ($n = 4{,}135$), using a subset of the respondents who answered items concerning digital assistants (survey form 1, $n = 2{,}045$). To our knowledge, this is one of the first publicly available surveys that asked about AI-algorithm consumption in the U.S. The original survey included a national sample of respondents aged 18 and over in the U.S. (Pew Research, 2017).

For those analyzed in Study 1, the median age category was between 30 and 49 ($M = 2.78$, recorded on a range of 1 = 18-29 to 4 = 65+, $SD = 0.97$), with slightly younger respondents than the U.S. population whose average age was 42 in 2015. The median household income was between \$50,000 and \$75,000 (6, $SD = 2.35$, measured on a range of 1 ≤ \$10,000 to 9 ≥ \$150,000). We do have close to equal representation in terms of gender (female 52.1 percent, coded as 1) and on average, the mean education category was some college experience ($M = 4.18$, recorded on a range of 1 = less than high school to 6 = postgraduate, $SD = 1.49$). As for race, nonwhites were 18.7 percent. We used these characteristics as predictors, and a binary coding was done with nonwhites as the reference group (1)—as in gender (female as reference)—to indicate a status of marginalized groups in the U.S. against which to observe outcome variables (access, use, and perception) in comparison (Sandvig et al., 2016). Still, using the category of 18.7 percent of the sample is limited in its variance. Thus, a caution is warranted in interpreting results related to race, as this binarity trades off sensitivities of observing various groups over parsimony of detecting a collective state in logistic regression.

4.1.1. Access and use: digital assistants

For the divide in the first- and second-levels, we used two measures. First, to measure access, we used a categorical measure that asked about the types of digital assistant devices that they had ever had/owned in their access to AI-based applications. This includes any AI-based applications inside devices, but excludes a stand-alone social robot, with the response options of (1) smartphone (89.7%), (2) a stand-alone home device, like an Amazon Echo or Google Home (18.5%), (3) computer or tablet (32.4%), and (4) some other type of device (6.1%). Second, to measure actual use of the devices, we asked "Do you ever use a voice-controlled digital assistant, such as Apple Siri, Amazon Alexa, Google Assistant, or Microsoft Cortana?" The answers were almost evenly split (Yes = 1, No = 0) ($M = 0.51$, $SD = 0.49$).

4.1.2. AI-positive and negative: perceptual understanding

Respondents were asked to indicate whether they perceived any of the following functional attributes for their use of AI-based digital assistants. For both positive and negative perceptual understanding, respondents were given three choices for their beliefs (major, minor, or no reason for their use/non-use of AI-based assistant device) and we created a binary measure for each item by collapsing major and minor reasons (No = 0/Yes = 1, having such understanding). Items for AI-functional positivity in its affordances include: (1) (Natural command) Spoken language feels more natural than typing ($M = 0.60$, $SD = 0.48$); (2) (Ease) It's easier for children to use ($M = 0.28$, $SD = 0.45$); and (3) (Fun) It's fun ($M = 0.61$, $SD = 0.48$). On the other hand, AI-functional negativity in its potential disadvantages was asked to those who did not use AI-based assistants. Items for AI-negativity include: (1) (Privacy) Privacy concerns ($M = 0.26$, $SD = 0.43$); and (2) (Difficulty) Too complicated to use ($M = 0.14$, $SD = 0.34$).

4.1.3. Results and discussion

To test our research questions and hypotheses, we constructed a logistic regression model predicting each criterion variable separately. Table 1 displays the results concerning H1a and H1b. The findings support the first- and second-level AI divides, with socio-demographics predicting greater chances of access as well as use. Higher levels of education and income were associated with higher use of digital assistants, and being younger and being nonwhite were also significant predictors, lending support to previous studies that found nonwhite groups stepped ahead in adopting certain digital platforms such as mobile-smartphone (Smith, 2013). On the other hand, different categories of people found markedly different as socio-demographic variations revealed interesting variations by social status with respect to the type of devices used for access.

First, income was noteworthy showing a positive relationship with the odds of having a stand-alone AI-based device such as Google Home. Being a woman also explained the lower chance of having a stand-alone AI assistant device, whereas older people were less likely to access AI on smartphone. Still, the interpretation is not straightforward, because it is difficult to see a clear quality difference among different types of AI-based devices. For instance, there is little reason to believe that a stand-alone device would be better off in benefiting users, the effect comparable to the apparent quality difference in the earlier form of Internet-based divide—broadband vs.

Table 1
Divide in access and use—Study 1.

Unweighted	Access to AI on different types of assistants [1]				AI Use
Socio-demographics	1: On a stand-alone device	2: On smartphone	3: On computer or tablet	4: On other type of device	Unitary item (Yes = 1)
Education	1.09	1.11	0.88*	1.04	1.07*
Age	0.84	0.72**	1.09	0.95	0.72***
Gender (woman)	0.69*	1.21	0.81	0.35***	1.03
Race (nonwhite)	1.37	0.85	1.36	0.88	1.27*
Income	1.13**	1.13	0.98	0.83**	1.13***
▲R^2	4.1%	3.9%	2.1%	5.3%	6.4%
Log likelihood	959.0 $n = 1057$ (those who use digital assistants)	663.4	1286.0	438.0	2653.3

*** $p < .001$,
** $p < .01$,
* $p < .05$
[1] Odds of logistic regression are reported, with 1 = access, 0 = no access to assistant on each specific type.

dialup. Nevertheless, the pattern of difference in our findings raises a concern about creating equal platforms for AI-based digital participation. Women, in general, tended to be behind with less access, and older people have not moved on yet to a ubiquitous smartphone platform and its AI use, such as Siri, as much as their younger counterpart.

Table 2 shows the results of two hierarchical logistic regression models that respectively examined positive perceptual understandings among digital assistant users, and negative understandings among non-users, with socio-demographics in the first block (H2), followed by access in the second block (RQ1). As expected, we found differences with age (Kumar & Lim, 2008), gender (Siegrist, 2000), and race (Smith, 2013). Notably, older people, when they did not use any AI-related devices, were likely to report that they stayed skeptical perceiving AI as difficult or too complicated. Men, on the other hand, were likely to show positive understandings, such as AI for being 'natural' and 'easy.' Among non-users, however, we did not find any gender difference, indicating that men, despite their greater level of use, might not be more alarmed about AI-related risk in their use of digital assistants.

Similarly, nonwhites, being earlier adopters with a higher level of use than whites, were more likely to understand digital assistants and their functions with the upside, but when we looked at those who did not use digital assistants, we found that nonwhites did not have an augmented concern such as privacy. In considering these differences, the findings regarding income and education were also interesting: (1) those with higher income were less likely to understand the AI-related functional features of assistants as positive, such as 'natural' and 'easy', whereas for those non-users, (2) people with lower income were more likely to understand its features as 'difficult', listing it as their primary reason for non-use. In other words, while those with higher income enjoyed better access and use, people with higher income also stayed skeptical about technological benefits when they chose not to use it, and this pattern was not the case for those who were not well off financially as they perceived the difficulty of digital assistant devices. The support for education was as expected; the educated people stayed more skeptical when its benefit was indicated by the functional 'ease,' for instance.

Finally, in terms of RQ1, we found robust influences of access in three dimensions of positive perceptual understandings (1.72, $p <$ .05, natural; 1.28, $p < .05$, ease; 1.72, $p < .001$, fun), illustrating that there is a relationship between the access-level and the perceptual-level disparities, with access harnessing general support for digital assistants. These suggest that the gap in perceptual understanding is being built upon the access divide that already exists on unequal terms, with exacerbating inequalities between those 'haves' and 'have-nots'. Collectively, it paints a grim picture: the difference in perceptual understanding can be deepened by social status, as lower income people, for instance, are not in the equal position to take advantage of their access to devices, to begin with. But even among those non-users, there was yet another divide, as those with lower income, unlike those who were well off, tended to understand AI only to be too complicated to use, thus missing out opportunities afforded in potential access and use of digital assistants.

Table 2
Predicting positive and negative perceptual understandings—Study 1.

Unweighted	AI-positive [1]			AI-negative [1]	
Step 1-Socio-demographics	Natural	Ease	Fun	Privacy	Difficulty
Education	1.00	0.89*	0.97	1.07	1.07
Age	1.25**	1.12	0.93	0.89	1.73***
Gender (woman)	0.60***	0.74*	0.81	0.83	1.01
Race (nonwhite)	1.55*	1.85***	1.25	0.98	0.69
Income	0.91**	0.90**	1.04	0.98	0.85***
▲R^2	4.6%	5.8%	1.0%	.08%	10%
Log likelihood	1343.0	1181.8	1360.9	1090.4	1048.4
Step 2-Access to AI					
Number of Device	1.27*	1.28*	1.72***		
Cumulative ▲R^2	5.3%	6.6%	4.7%		
Total Log likelihood	1337.0	1175.8	1332.5		
	n = 1057 (those who use digital assistants)			n = 983 (those who do not use)	

*** $p < .001$,
** $p < .01$,
* $p < .05$
[1] Odds of logistic regression are reported, with 1 = Yes, 0 = No to each of specific reasons.

4.2. Study 2: data and measures

Data for Study 2 were collected from U.S. respondents, who were recruited online in 2019 (the age of 18 and above) by Dynata using a Qualtrics platform. From an initial sample of 1,200, we removed respondents who failed in an attention-check question, and those with more than 80% of unfinished items were also eliminated, leaving the final sample of 753 respondents. Descriptive statistics show that demographic characteristics in the final sample are close to figures reported in the U.S. 2015 American Community Survey (ACS). Females were 54.8% (ACS = 51.4%); the median income category was 4 with $50,000 to $74,999 (ACS = $53,889); the average level of education (the range of 1 to 5) was some college, with $M = 3.28$, $SD = 1.08$ (ACS = some college); and the mean age was 46.47 (*Min.* = 19, *Max.* = 87, $SD = 15.43$) (ACS = 45–54 years).

4.2.1. Access and use: digital assistants

Similar to Study 1, we employed two separate measures. To measure access, we asked if respondents had access to any of the following AI-based assistants: Amazon Alexa or Echo, Google Home, Apple Siri, Samsung Bixby, Sony Aibo, TikTok, or any other similar AI robotic products. The number of AI device ownerships was counted to generate a measure of AI access. With 28.8% of respondents owning at least one device, the possible range for access was 0-7, and the observed mean was 0.68 ($SD = 1.14$). In terms of actual use, we used an item that asked the frequency of use. The wording was: "If you check YES for any of the above [AI-based assistant devices], how often do you use?" The respondents were asked to indicate their frequencies on a scale of 1 (never) to 5 (several times a day), with $M = 1.84$ and $SD = 1.45$.

4.2.2. AI-positive and negative: perceptual understanding

As in Study 1, dependent variables of main interest are positive and negative perceptual understandings related to their use of AI-based personal devices. While the perceptual measures in Study 1 tapped more into the general support for hardware-based functional features, the focus of Study 2 is on the informational aspect of AI-applications, namely, AI-processed personalized and recommended decisions. To assess AI-informational positivity, we used six items asking respondents to rate their perceptual understanding about AI in its affordance of accuracy on a five-point scale (from 1 = not at all to 5 = extremely). The items included: (a) a bank using AI to determine the best banking products to offer, (b) the use of AI to provide personalized recommendations on items for purchase, (c) a doctor using AI to help make a better diagnosis or recommendation, (d) a judge using AI to help make a better legal decision, (e) an insurance company using AI to monitor and analyze your daily activities, and (f) the government using AI to provide personalized public services. All six items were summed to create an index (AI-informational positivity: accuracy, $M = 15.51$, $SD = 6.04$, ranged

Table 3
Predicting access, use, positive and negative perceptual understandings—Study 2.

Unweighted	Access	Use	AI-positive	AI-negative
Step 1-Socio-demographics				
Education	0.02	0.03	0.03	0.08*
Age	-0.38 ***	-0.33***	-0.24***	0.18***
Gender (woman)	-0.10**	-0.08*	-0.12**	-0.03
Race (nonwhite)	0.14***	0.10**	0.10**	-0.00
Income	0.13**	0.11**	0.01	-0.04
▲R^2	18.6%	13.8%	7.0%	3.6%
SE of estimate	1.03	1.35	5.79	3.32
Step 2-Access to Digital Assistant				
Number of Device			0.29***	-0.07
Cumulative ▲R^2			14.2%	3.9%
SE of estimate			5.57	3.32
Step 3-Use				
Frequency of Use			0.22**	-0.10
Total ▲R^2			15.4%	4.0%
SE of estimate			5.53	3.31

*** $p < .001$,
** $p < .01$,
* $p < .05$

from 6 to 30, $\alpha = .91$).

To assess AI-informational negativity, we used four items asking respondents to estimate their concern about AI resulting in potential threats of data surveillance. A 5-point scale (ranging from 1 = extremely unlikely to 5 = extremely likely) was used in each of the four concerns: (1) greater access by companies/gov. to info about people, (2) increase in monitoring, (3) increase in data collection of digital habits and activities, and (4) little control over information collection in daily life. We added these four items to create an index (AI-informational negativity: concern, $M = 16.87$, $SD = 3.38$, $Min. = 4$, $Max. = 20$, $\alpha = .90$). The distinction between AI-informational positivity and negativity is important to note. Conceptually, the distinction draws upon traditional debates regarding the tradeoff between the needs for data privacy (concern) and accurately-tailored processing (accuracy) (Gandy & Nemorin, 2019). As we recognize two dimensions, the aim was to measure how people's understanding of conflicting needs (i.e., AI data surveillance for accurate-processing of a person) fare perceptually in their actual exposure to AI-based personal applications. [2]

4.2.3. Results and discussion

Table 3 presents the results of hierarchical OLS models that tested systematic relationships between socio-demographics, access (H1a), use (H1b), and perceptual understanding (H2). We highlight the results in comparison to Study 1. First, we found that a person's socio-demographic backgrounds were more explicitly related to access than Study 1. All socio-demographic variables significantly predicted differences in having more access (H1a), yet with only education displaying no direct relationship. Second, socio-demographic inequalities in use (H1b), as found in Study 1 (conducted at an earlier year 2017), was echoed in Study 2 (conducted at a later year 2019), which indicates that those differences may not be due to a chance alone. In fact, the patterns, in which one's backgrounds of age, income, gender, and race related to use, were persistent. Nonwhites as in Study 1 were more avid adopters and more frequent users of digital assistants than whites. Being younger, being financially well-off, and being men were also found to be the predictors for the frequent use. Similar to access, however, education displayed no effect, even if the block of socio-demographics explained relatively sizable variations of use (13.8%) and access to digital assistants (18.6%).

Fundamentally, the findings commonly found across two studies suggest the alarming insight that inequalities we witnessed in the previous form of Internet-based divide are being repeated for a new form of AI-driven digital participation on the first- and second-levels (Gran et al., 2020). In fact, this was also true of the level of perceptual understanding, as we replicated the findings of Study 1 in predicting the presence of perceptional understanding beyond the material context of access and use. That is, there were socio-demographic variations on the formation of positive understanding (AI-informational positivity). Younger people, men, and nonwhites were more likely to see AI-generated information in various applications as accurate, and these patterns for affirmation were exactly the same as in Study 1. On the other hand, we also found reduced variations by socio-demographics in terms of AI-negative (AI-informational negativity)—similar to Study 1, suggesting that critical reception of new technologies, like AI-based applications, may be reserved yet only to certain social positions.

In this context, the influences of education and age on perceptual understanding were noteworthy. For instance, those with higher education were able to critically view AI-generated recommendation as having an issue related to privacy violation. Also, as in Study 1, older people were more likely to perceive a threat of AI generated information. This is an important finding, which suggests that while younger people were actively involved in terms of access and use, they did not seem to evaluate or utilize information critically at all—the result in line with prior studies (Van Deursen & Van Dijk, 2014). Similarly, the finding that nonwhites and men, who were avid adopters as well as frequent users of digital assistants, were more likely to believe in AI-informational positivity raises a concern; their active consumptions occur in the absence of a balanced viewpoint about data risk that AI generated information and digital assistants can impose. The lack of significance for income, in particular, warrants attention in this regard, since those with better resources did not necessarily fully accept AI-informational positivity. That is, when we place the perceptual gap on top of unequal access and use, it becomes clear that only a subset of socio-demographic groups, typically born out of preexisting sociocultural advantages, affords a healthy and balanced acceptance of AI-generated information and digital assistants, which enables one to understand its risk as well as benefits.

The bottom of Table 3 shows the results pertaining to RQ1. We found significant connections between the access-, use- and perceptual understanding-level disparities, with access and frequent use harnessing the support for AI-informational positivity. No equivalent relationships were found for AI-informational negativity, as there was a marginally significant negative relationship between access and AI-informational negativity. We tested this divergent pattern between AI-informational positivity and negativity with an eye toward how access is indirectly linked to understandings through the use of digital assistants. The results summarized in Table 4 indicate that greater access is related to more active use, which in turn translates into positive perceptual understanding. However, we found no comparable indirect relationship for concern. Together, these results suggest that the first-level (access) divide, while significantly interlinked to the second-level (use) divide, takes a distinctive route to transfer (dis)advantages to the perceptional

Table 4
Indirect relationships between access and reception—Study 2.

DV		B (SE)	95% Confidence	
			Low	High
AI-Positive	Access Use Accuracy	3.39 (1.02)	1.36	5.35
AI-Negative	Access Use Concern	-0.18 (0.60)	-1.41	1.00

understanding. Put differently, access alone, though necessary to participate in AI-based platforms, such as digital assistants, will not suffice to promote a critical reception of AI-generated information, as a balanced viewpoint about risk (concern) and benefit (accuracy) seem not solely grounded upon technological access and use bases.

4.3. Interactive effect of education: study 1 and study 2

With respect to RQ2 that asked the roles of education in its interaction with other socio-demographic factors producing perceptual-understanding gaps, the results in Study 1 revealed several important patterns. First, we found that education interacted with income, supporting our expectation that a class distinction, which is primarily based on education and income (Bourdieu, 1984; Van Dijk, 2020), lays the fundamental ground for the difference in the perceptual understanding of technologies including AI information and

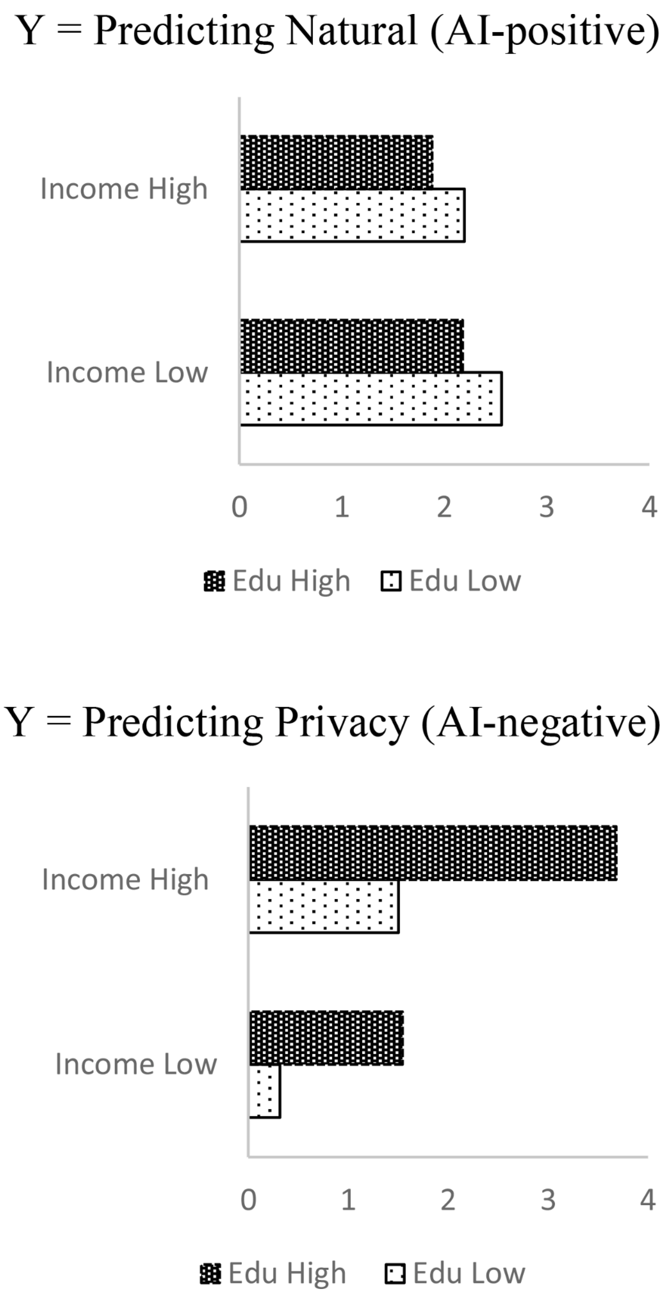

Fig. 2. Interaction: income (x1) and education (x2)
Note. We used odds ratio to plot combination of 1 (high) and 0 (low), bars indicating likelihood of having positive or negative perceptions, respectively among AI users and non-users.

digital assistants. Second, the interactions diverged between positive and negative perceptual understandings. Education interacted with income to explain higher AI-informational negativity, but to predict decreased AI-informational positivity among those with higher income, as we found respective patterns of interactions for AI-informational negativity (privacy, Beta = -0.04, ratio of 0.95 $p < .05$, with education, 1.22 *n.s.* and income, 1.18 *n.s.*, constant = 0.31), and for AI-informational positivity (fun, Beta = 0.04, ratio of 1.04 $p < .05$, education, 0.92 *n.s.* and income, 0.86 *n.s.*, constant = 2.48; ease, Beta = 0.06, ratio of 1.06 $p < .01$, education, 0.84 *n.s.* and income, 0.71 $p < .001$, constant = 1.31; and natural, Beta = 0.06, ratio of 1.06 $p < .01$, education, 0.68 *n.s.* and income, 0.69, constant = 12.92 $p < .001$).

Figure 2 shows this contrasting pattern between positive (natural) and negative (privacy) perceptual understandings. The upper panel shows that among users of digital assistants, the likelihood of having a positive perception decreases—among higher income people when the level of their education gets higher. The pattern is precisely the opposite among non-users plotted in the lower panel, because the likelihood of having a negative perception is even more likely to increase for those with higher education when they are financially well-off.

We failed to find equivalent effects among respondents of Study 2. Statistically, the lack of interactions might stem from robust main functions of socio-demographics, as compared to those found in Study 1.[3] Conceptually, it can indicate that difference in perceptual-understanding in the later year might have not hinged upon subtle socio-demographic interaction as much as in the earlier year, as the ownership of AI-based digital devices had increased over time. In other words, perceptual differences based on socio-demographics may have begun to congeal in their respective right, with wider diffusion of access and use as seen in Study 2. Importantly, however, this also indicates epistemological limitations of surveys that cannot discern the 'transformative' nature in our object of inquiry. The perceptual shift may have been detected via in-person observation—researchers interacting with respondents over time to observe how their practices might have varied through their device (non)ownership (Seaver, 2017).

Surely, the panel dataset over time will ascertain to sort out the best interpretation. Even when we count further complex possibility, it is clear that interactions within socio-demographics seem deepening existing inequalities, making marginalized populations (in this case, those with low income and low education) more susceptible to potential data pitfalls of the use of digital assistants and we are concerned that this is manifest at an early stage of its technological diffusion. The fact that the perceptual, not just access and use, difference can emerge based on income and skewed toward a particular viewpoint appears astounding. Simply put, we have evidence that there are more constructive social environments that help incubate the critical acceptance on the level of perceptual understanding, whereas other conditions falling behind education and income promote naïve viewpoints in the actual consumption of AI generated information and digital assistants.

5. General discussion

We analyzed data from two studies based on national samples of two years (2017, 2019), with their respective emphasis on AI-related functionalities (Study 1) and AI- recommended information (Study 2) in people's access and use of digital assistants, such as Google Home, Amazon Alexa, Echo, or Apple Siri. We drew upon the insights from digital divide literature (DiMaggio et al., 2001; Neuman et al., 2011; Van Dijk, 2020; Van Deursen & Helsper, 2015) to better understand the reproduction of inequalities at the levels of perceptual-understandings, as well as access-use, as manifested in various functional-informational forms of AI-related consumption in digital assistants. The empirical evidence presented in this work points to the tremendous power of socio-demographic status in reinforcing social cleavages in terms of access and use of AI-assistants, with this pattern consistent in both datasets of Study 1 and Study 2. Additionally, we posited the possibly recursive interconnections among respective divides, and found that material-based ownership access (the first-level) and exposure-based actual use (the second-level) gaps are related to, if not conducive of, the perceptual-understanding gap, perpetuating systematic inequalities and eventually, congealing the patterns in their loops.

With these findings in mind, we provided important insights into social dynamics of how access, use, and perceptual understanding toward emerging technologies like AI, in interface with such personalized devices as digital assistants, began to develop. There are at least four issues in the divide context of AI-functional and informational consumption: (1) there is an access-use barrier that is worsening preexisting offline socio-demographic inequalities; (2) these patterns of inequality repeat the divide previously observed in the adoption of Internet; (3) there are further emergent perceptual divides along with income, education, race, age, and gender, and (4) the perceptual divergence occurs in a way that positive perceptual understandings, of both functional and information aspects of AI, are more preponderant of marginalized groups—especially those with low income and low education. These insights are characteristically extending critical and reserved viewpoints about algorithms as previously expressed by two lines of scholarship—namely, (1) risks of losing autonomous control and privacy (Airoldi, 2021; Cheney-Lippold, 2018; Christin, 2020; Seaver, 2019, critical algorithm studies) and (2) likely victims of those disadvantages AI-based devices pose as they are hidden from the public (Cotter & Reisdorf, 2020; Gran et al., 2020; Klawitter & Hargittai, 2018; Lutz, 2019, digital inequality).

Taking more theoretical takes on our findings, the newer insight is that digital divide is now spilling over 'horizontally' across different technologies (broadband, IoT, AI, etc.) and 'vertically' across different levels (access, use, perceptions, etc.), as we manifested its trend in the use of digital assistants. Consistent with previous literature examining the third-level divide in the case of Internet, our findings reveal that higher education and income levels were associated with producing better outcomes (DiMaggio et al., 2001). Notably, the non-significant role of access in promoting or encouraging perceptual understanding of AI-informational negativity (Study 2) supports the idea that the critical receptance of technologies would not be necessarily a product of natural technological cycle, i.e., starting from owning a device, starting to use it frequently, and then, developing a somewhat balanced understanding, as each level of inequality reinforcing each other remains deeply embedded in the recursive cycle of socio-demographic environments. That is, instead of subscribing to a technology-centric paradigm that would put AI-technologies as a single determinant for socially-enabling power, our findings from two datasets suggest that the direction may be reversed with societies largely facilitating or limiting AI-based consumption like digital assistants, not the other way round. (Beer, 2017; Neuman, 2016; Van Dijk, 2020). This lends support to our thesis that inequalities arise and linger based on perceptual lens through which people understand social realities of a new technology, given that the acceptance and consumption of a technology not only differs across social status but also reproduces its social power (Bourdieu, 1984; Lamont, 2012).

Fundamentally, this begs a profound question on how to undo the reproducing mechanism of the Matthew effect if a small segment of any given society actually occupies better positions to utilize new technologies more cautiously and if this tendency persists over time (Bourdieu, 1984; Neuman et al., 2011). For a moment, we can set aside apparent advantages for those well-off who can buy better and more AI digital assistant products, as some might shrug off to foresee a market-based solution in which prices drop eventually. Still, the fact that the perceptual difference arises based on gaps in income and other sociodemographic conditions such as education insinuates that the precise path of social influence may be enclosed in tight socioeconomic boundaries, thereby possibly blocking the flow of other viewpoints. One distinctive feature with respect to technological diffusion is the intermediary role of early adopters who serve as interpersonal conduits disseminating information about technologies within their social parameters (Beer, 2017). As wider diffusion of AI, especially via its more approachable forms such as digital assistants, sooner or later shrinks the access-use level divide, we will need to investigate the ways in which these social barriers will become fluid so that social status does not correlate with narrow sets of positive or negative viewpoints in isolated perceptual bubbles.

Three important connections to this issue merit further discussion. First, we underscore the idea that technological reception may not always coincide with the acceptance at the level of perceptual understanding. Nevertheless, we continue to have little idea of how to identify precise socializing patterns upon which a status like being nonwhite—while enjoying better access—is little inclined toward critical understandings about AI. A meso-level scrutiny of interpersonal channels, such as churches, that are unique to communities may help future studies uncover how particular environments shape public perceptions by filtering out certain viewpoints. Second, our findings may speak to the idea of a technological issue cycle. That is, as a new technology becomes widely diffused, it will enter a mature phase where perceptions about its risk or benefit are saturated. Literature indicates that technologies often start off with hype and enthusiasm, quickly followed by negative perceptions and criticism before it is fully embraced (Wildavsky & Dake, 1990). We do not know yet whether AI or its versions at the exposure to digital assistants will ever enter those issue dynamics and if so, temporally what stages of the dynamic this study captured. Third, spatially speaking, our datasets are limited in the U.S. context. This may pose a threat to the generalizability of our findings because we are dealing with perceptual differences that are contingent upon cultural norms and values, which might be uniquely different among populations even within a national context, laying the different conceptual justifications and skills over the use of technological artefacts.

In that regard, our second-level divide measure, only with the use at the point of device exposure, does not include skill that might turn out to be even more critical capital that differentiates perpetual understanding equipped with critical evaluation. Future studies should thus validate this study's findings in terms of AI-related skills to see whether variations found in this study would persist under organizational settings that are bounded with specific workplace practices and social norms (Van Laar et al., 2020). Those efforts should also consider national-cultural contexts (Van Deursen et al., 2021, IoT in Netherland population), in-depth qualitative measurements, and other forms of algorithm skills that are germane to a specific digital platform, such as Facebook, as opposed to general measures of material or device-based access.

Footnotes

1 This is a simplified classification, given to users, two are most perceptible part of AI operation mechanically hidden inside. Accordingly, AI can be defined in its socio-cultural relation to users/non-users (Hargittai et al., 2020), how people come to access/-perceive in their actual exposure to particular artefacts—as in our case of relative lack of hardware access, use, as well as perceived harms/disadvantages and affordance (i.e. of recommended function and information), rather than what it is (ontological state), how it operates, or what it carries. We appreciate reviewers' insight for this clarification.

2 Scholars operationalized digital skills in various domains, using varied measures of activities, cognition, knowledge, content-production, etc. Although this study does not use explicit skill items, our DV is closer to perceptual skill—implicit understanding or knowledge acquired from use/access, as well as one's socio-demographic environment (Lamont, 2012). For the risk of digital assistants, for example, Study 2 captures perceptual part of ability or skill to understand losing autonomy (as in the item of 'having little control').

3 Increased statistical variance over time may have contributed to widened socio-demographic variations found in Study 2. That is, there was a small proportion of stand-alone digital assistant users (18.5%) in Study 1 (2017), as compared to 28.8% in Study 2 (2019). While this is a possibility, we cautiously point consistent findings regarding socio-demographics over time, as in the case of lower income people falling behind in all three divide levels. This is in line with prior studies (Hargittai, 2002; Van Deursen et al., 2021) that measured the extent of first- and second-divides in other devices such as IoT, mobile, and Internet-broadband, which indicate that widened socio-demographic variations in Study 2 might have not been attributed to statistical idiosyncrasies alone.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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