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A Status Report on the Use of and the Attitudes Towards ChatGPT in Dutch Society

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Samenvatting

Is de AI-revolutie al begonnen? Een statusrapport over gebruik en perceptie van ChatGPT in Nederland

Dit paper onderzoekt kennis, gebruik en percepties over ChatGPT onder de Nederlandse bevolking in de *early-adoption phase*. Ongeveer de helft

heeft kennis van ChatGPT en 1 op de 10 heeft het gebruikt. De impact van ChatGPT wordt gemiddeld als groot en negatief gezien, waarbij eerder gebruik van ChatGPT de voornaamste voorspeller is van positief gepercipieerde impact.

Abstract
The launch of ChatGPT led to a fast-growing userbase and substantial attention from journalists and academics towards the developments, possibilities and threats of AI. Despite this, we have little to no knowledge about the diffusion or perceptions of ChatGPT in the general public. Using a representative sample of the Dutch adult population (N = 1,489), we probed in the early adoption phase the public's knowledge, use and perceptions of ChatGPT. Little more than half of the respondents knew about the chatbot; only 1 in 10 had already used it. Likely early adaptors of new technology (younger, male, higher educated) were more aware of ChatGPT. The impact of ChatGPT was on average perceived to be large and negative, with prior use being the main predictor of a positive perceived impact. We discuss these findings in light of previous literature on new technology use, and propose directions for future social scientific research on the use of AI.

Keywords: ChatGPT, artificial intelligence, adoption of new technologies, perceived consequences of new technologies

Introduction[1]

In November 2022 the organisation OpenAI launched its chatbot ChatGPT. Trained using self-supervised learning on vast amounts of textual data, the model behind ChatGPT (GPT-3.5) was developed as a general-purpose language model capable of generating text in response to a wide range of prompts. It can write, for example, in various languages, poetry, essays in the style of known authors, computer programming scripts and sarcastic jokes; compose music; play games; and imitate operating systems (Thorp, 2023; Van Dis et al., 2023). With its ground-breaking approach, the wide range of new affordances, and free public access, ChatGPT became a global hit in less than two months. As of 4 December 2022, ChatGPT had amassed over one million users. By January 2023, its user base had surpassed 100 million, making it the fastest-growing app in history (Hu, 2023).

In a short time, ChatGPT gained much attention from journalists, scholars and all sorts of expert and non-expert users. The bot has been hailed by many and described as a 'breakthrough' with the potential to 'change our mind about how we work, how we think, and what human creativity really is' (Thompson, 2022). But it has similarly sparked controversy, for example, among scientists and educators who worry about AI-based plagiarism in scientific work and education (e.g., Thorp, 2023), and also because it has been demonstrated that ChatGPT, on several occasions, created false and erroneous responses, for example about knowledge questions (e.g., Pearl, 2022) and summarising research articles (Van Dis et al., 2023).

Research into the diffusion of technologies throughout society indicates that the spread of new technology goes through different stages in which individuals first become aware of an innovation and eventually decide whether or not to adopt it (Rogers, 2003). In the current so-called early adoption phase (Rogers, 2003), an important aspect of ChatGPT might be its *trialability* (i.e., the degree to which an innovation can be experimented with before adoption). In addition, vast news and social media attention on ChatGPT may potentially both accelerate elements like knowledge about and trialability of ChatGPT itself and also raise awareness about personal and societal consequences of this new technology.

Despite the fast-growing user base of ChatGPT and the potentially widespread positive and negative societal consequences of the bot, we have little to no knowledge about the diffusion of ChatGPT among the general public in this early adoption phase. It is still unknown which segments of the general public know about ChatGPT, who uses it, and for which reasons. In addition, we still have little understanding of how the population views the potential impact of ChatGPT in this early phase: Is the impact of ChatGpt expected to be profound or marginal, and are changes anticipated to be more beneficial or more detrimental to society? Although adoption to new technology is a longitudinal process, it is important to get a clear picture of the how and the who in this early adopting phase.

In this preregistered explorative study, we address these questions among a representative sample of Dutch adults. More specifically, in a survey launched end of January 2023, we asked Dutch participants about their ChatGPT (1) knowledge, (2) frequency of use, (3) purpose of use and (4) perception of societal consequences. In this paper, we explain variation in ChatGPT knowledge and perception of societal consequences based on

who respondents are (i.e., demographic variables), where and how often respondents consume news (i.e., media use) and the degree to which they trust institutions that are responsible for the development and the guiding of these innovations (i.e., institutional trust). The preregistration of the study can be found here: https://osf.io/yd4fk.

Technology Adoption

When a new technology is introduced into society, its adoption into societal members' everyday lives has been distinguished along two lines: First, different stages of adoption have been identified ranging from awareness of the technology, through the first use to the integration of the technology into everyday life and use for different purposes (e.g., Haddon, 2006; Rogers, 2003). This could be summarized with the question: *How* is a new technology adopted? Second, previous research has shown that different segments of the population adopt technology at a different pace (e.g., Dedehayir et al., 2017; Rogers, 2003). This can be summarized under the question: *Who* adopts a new technology?

To explain *how* a technology is adopted, the prominent diffusion of innovation framework by Rogers (2003) describes the stages of awareness (the individuals knows about the innovation), persuasion (the individual forms an attitude towards the innovation), decision (the individual decides to adopt/not adopt an innovation), implementation (the individual tries and uses an innovation) and confirmation (the individual examines the use of the innovation and continues to use the innovation). Given that ChatGPT was introduced only two months prior to data collection of this study, the adoption process can be considered to be at an early stage. However, with technological innovations being introduced at a higher rate and with faster communication processes, also adoption processes could be accelerated (Atkin et al., 2015). This is indicated by ChatGPT being the fastest-growing app in history (Hu, 2023). This faster pace makes it particularly interesting to study the adoption of ChatGPT in an early stage.

Research on Roger's diffusion of innovation theory was criticized for focusing mostly on the adoption decision itself and not including post-adoption processes (García-Avilés, 2020). As for at least in part free online-access tools such as ChatGPT, adoption does not end with a buy or not buy-decision and given the flexibility of tools such as ChatGPT, focusing not only on an adoption-decision but also on for what purposes it is used and how frequently is important (Atkin et al., 2015). To explore the status of ChatGPT adoption

in Dutch society two months after ChatGPT's introduction, we will therefore descriptively assess the status of awareness, use (once versus frequently) and the purposes of use of ChatGPT.

To explain *who* adopts a technology, studies and frameworks usually study different groups of society who adopt an innovation earlier or later. As it is of interest to both marketers of new technologies and research on the digital divide, much research has identified which factors predict technology awareness and early adoption (García-Avilés, 2020; Lutz, 2019). In this study, we will focus on sociodemographic factors, political orientation and news media use.

Previous studies have shown that early adopters of technologies tend to be male, younger and more highly educated individuals (Dedehayir et al., 2017, Lutz, 2019). Moreover, studies have indicated that progressive individuals tend to adopt innovations earlier than conservative individuals (e.g., Sigrin et al., 2015. P),olitical orientation and other demographic variables were not as influential as could have been expected in areas such as the adoption of environmental-friendly technologies (Palm, 2020).

As a final predictor of adoption processes, we will focus on news media use. Rogers (2003) assumes that individuals with more extensive news exposure adopt an innovation relatively early in the diffusion process. According to Rogers (2003) predictions, studies have found that news use is related to adoption (e.g., Toole et al., 2012). While this has traditionally included traditional news media, the current media landscape also emphasizes news which are used on social media platforms as an additional important source of knowledge about innovations (Atkin et al., 2015).

Taken together and building on factors previously shown influential for adoption processes, we explore in this study, the demographic factors of age, sex, level of education and political orientation as well as the factors of news consumption and institutional trust and their influence on ChatGPT familiarity.

Perceived Societal Consequences of ChatGPT

ChatGPT is assumed to be a revolutionary technical innovation with profound impact on society (Bockting et al., 2023). The literature on moral technology panics has identified societal members' attitudes towards technologies as an important driver for political regulation (e.g., Orben, 2020).

Moreover, social constructivist viewpoints on technology use have established that perceptions of technology use as generally positive or negative can impact the effect of technology use on the individual (e.g., Wolfers et al., 2023). Already early studies showed high levels of risk perception concerning new technologies among the general public (Pilisuk et al., 1987). Perceived influence on society can be distinguished along two lines: First, the perceived influence of a new technology on society can be perceived as small or large meaning the *size of impact* can be judged differently. Second, the influence on society can be perceived to be positive or negative, summarized in the concept *valence of influence*.

The amount of research on individuals' judgement on the perceived *size of influence* of a new technology on society is surprisingly limited. Although, already early research studied the valence of public opinion of new technologies (e.g., Pilisuk et al., 1987), the perceived degree of influence has been seldomly studied.

Previous research on the *valence of influence* has shown that certain social groups have a more optimistic view on technological impact. Demographic factors shown to impact the perceived valence of impact include sex/gender (Pilisuk et al., 1987; Venkatesh et al., 2003), age (Venkatesh et al., 2003) and education (Burton-Jones & Hubona, 2005). Political orientation was also shown to relate to more optimistic or pessimistic judgment of new technologies (Molina & Sundar, 2022). In these predictors, we recognize the same as those that are likely to predict being knowledgeable of new technologies. Moreover, prior use was shown to be related to more positive technology attitudes (e.g., Varma & Marler, 2013) which we will assess as additional predictor.

In addition to these predictors, we also focus here on institutional trust, as this has been shown to be an important factor in individuals' perceptions of technological risks (Renn & Benighaus, 2013). Given that user behaviour and responses to ChatGPT are likely used for further training of the language model, trust in different actors who can ensure that data is protected is important (Jo, 2023). In this study, we will focus on trust of institutional actors that are responsible for the development of new technologies, but also can be held responsible for protecting against negative consequences of new technologies: government, science and BigTech companies.

Finally, literature on moral technology panics assumes that news media play an important role in moral panic creation, meaning that the news media's

reporting on technology risks should be associated with an individual's judgment on the valence of technologies' influence on society (Hunt, 1997; Renn & Benighaus, 2013). Studies in this field have mostly focused on content analyses showing that news media reporting about new technologies are often negative and risk-focused (e.g., Stern & Burke Odland, 2017; Vanden Abeele & Mohr, 2021). We add to this literature studying whether news exposure both to traditional news outlets and on social media predicts perceived impact of ChatGPT on society.

Given the supposedly considerable influence ChatGPT could have on society and given how increasingly important regulations of technologies are, we explore in this study which factors predict the valence of impact as well as the expected size of impact. As factors predicting the perceived influence we focus on the same set of predictors as for the adoption of use which were similarly discussed as important drivers of public opinion towards new technologies, namely demographic factors, new media use, institutional trust and prior use.

Methods

Participants and Procedure

For this study, we collected cross-sectional data from 1,820 individuals from the Netherlands. The fieldwork was conducted between 30 January 2023 and 12 February 2023 by a research company (I&O Research, www.ioresearch.nl). The sample was drawn such that it would match the Dutch population in age, gender and education. After removing speeders (n = 24), straightliners (n = 181) and participants that failed two attention checks (n = 168), our final sample consisted of 1,489 participants (47.8%)[2]. For data exclusions, we followed a preregistered protocol (https://osf.io/7r36v). The age of people in the sample varied between 18 and 88 years (M = 53.33, SD = 16.08), and about 40.6% of participants had some type of higher education.

The data was part of a three-wave collaborative study, which included cross-sectional and longitudinal projects (https://osf.io/d958h). The complete survey included items about a variety of topics. An overview of the items that were included in the survey can be found here: https://osf.io/d958h and https://osf.io/7r36v. For the current study, we included items measuring people's perceptions towards ChatGPT and items on institutional trust in the second wave of the survey. In addition, in our analyses, we also use several

background characteristics retrieved from the research company's database (i.e., demographics) or measured during the first wave of the collaborative survey (i.e., political orientation, news consumption).

Measures

Perceptions towards ChatGPT

Familiarity with ChatGPT. To measure people's familiarity with ChatGPT, we asked them whether they had heard of ChatGPT before. Participants could answer (1) *no, I have never heard of it,* (2) *yes, I have heard of it but did not try it,* (3) *yes, I have already tried it once or a couple of times* or (4) *yes, I have used it regularly.*

Purpose of Use ChatGPT. We asked those who had used ChatGPT before about the purpose of their use ('What did you use [ChatGPT] for?'). Participants could choose one or more of the following options: (1) *to have fun with it,* (2) *to do my homework/or for my studies,* (3) *for work-related tasks,* (4) *for computer coding,* (5) *for writing text,* (6) *for asking questions about factual information,* (7) *for advice related to your personal life*. Participants could also include their answer via an *other* (8) answer option with an open text box. Thirty-five participants used the 'other' category, of which 31 answers could be recategorized into one of the original 7 categories. Data from the remaining 4 participants were omitted, because their answers could not be categorized.

Perceived Consequences of ChatGPT. We used two items to measure the perceived consequences of ChatGPT ('How do you perceive the consequences of ChatGPT. ChatGPT will . . .'). The first item measured the size of impact people believe ChatGPT will have on society and ranged from (1) *have no effect on society at all* to (7) *will have a large effect on society*. The second item measured the valence of this effect and ranged from *make society worse* (1) to *make society better* (7).

Predictors

Demographics. As demographics, we used age, sex, level of education and political orientation. Information related to age, sex and level of education were retrieved from the research company's database. Age was measured in years and for sex participants had to indicate which sex was included in their passport (*male*, *female*, *X*; recoded as *female* = 1, *non-female* = 0). For level of education, participants were asked to indicate their level of education

from 7 categories (e.g., *no education*, *university bachelor's, etc.*). Following the standard from Statistics Netherlands (Pleijers & De Vries, 2021), we recoded this variable into 3 categories: *lower level of education* (1), *medium level of education* (2), *higher level of education* (3). Political orientation (M = 5.95, SD = 2.32) was measured in the first wave of the collaborative survey by asking participants to rate their position from *conservative* (0) to *progressive* (10). For this item, we allowed participants to answer they *don't know* (or *do not want to answer*) their political position, which led to 76 missing values.

Type of News Consumption. Two types of news consumption variables were created. The first was a measure for traditional news consumption (M = 2.28, SD = 1.45). This variable was a sum score of 21 items measuring the number of days people, in a given week, consume particular news outlets. The sum scale included 8 national newspapers, 11 news websites and 2 national television news sources. We divided the sum score by 7, with the final measure indicating how many of these news outlets respondents use on average per day. The second variable measured social media news consumption (M = 0.72, SD = 0.55). This variable was a mean score of ten items, ranging from *never* (1) to *almost always* (7), measuring how often participants felt they encountered news or searched for news when they used various social media platforms (e.g., WhatsApp, Telegram, TikTok).

Institutional Trust. In this study, we measured 3 types of institutional trust (e.g., Van Spanje & Azrout, 2020). Trust in government (M = 3.12, SD = 1.56), trust in science (M = 5.52, SD = 1.27) and trust in Big Tech (M = 3.03, SD = 1.42). Trust was measured with single-item statements ranging from *no trust* (1) to *a lot of trust* (7). Also, for institutional trust, we allowed participants to answer they *don't know* their level of trust per institution, which led to 118 extra missing values (government: $n_{missing}$ = 4; science: $n_{missing}$ = 19; Big Tech: $n_{missing}$ = 107).

Results

Familiarity with ChatGPT

Out of our 1,489 respondents, 43.9% (n = 654) had never heard of ChatGPT. A slight majority of our sample (56%; n = 835) had heard of it (see Figure 1). Nonetheless most of those that knew ChatGPT had never used it (45.6%; n = 679). Only a small part of the sample had tried it either once or a couple of times (8.3%; n = 124), and an even smaller proportion had used it regularly (2.1%; n = 32).

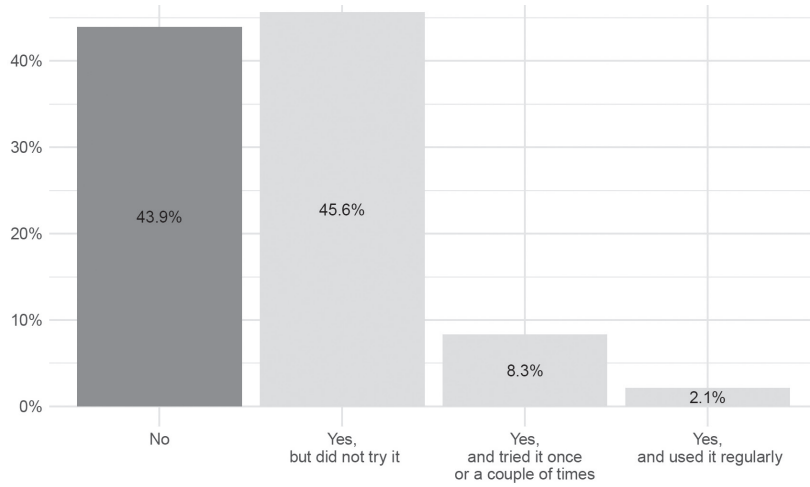

Figure 1. The extent of familiarity with ChatGPT

To better understand who knows about ChatGPT, we merged the three categories in which the respondents indicated they knew about ChatGPT. This dichotomy, indicating whether or not respondents knew about ChatGPT, was subsequently used as the dependent variable in a logistic regression.[3] The results of this analysis are presented in Table 1.

As shown in Table 1, in terms of demographics, we observed that younger (vs. older) individuals were more likely ($p = .025$), and females (vs. non-females) were less likely ($p < .001$), to know about ChatGPT. Education also played a role, with higher (vs. medium) educated individuals being more aware ($p < .001$), and lower (vs. medium) educated individuals being marginally less aware ($p = .050$), of ChatGPT. Those who perceived themselves as more progressive (vs. conservative) also had a higher likelihood of knowing ChatGPT ($p < .001$). Consumption of news via traditional media also predicted a higher likelihood of knowing about ChatGPT ($p < .001$), but we found a non-significant effect of news consumption through social media ($p = .157$).

As the actual sizes of coefficients from a logistic regression are hard to interpret in terms of their substantial meaning, we also calculated the expected proportions at different values of the predictors and the differences between those expected proportions (see the last two columns of Table 1). For the dummy variables, we compared that category with the references category. For the scale variables, we focused on the predicted proportions of knowing about ChatGPT by the predictors at their means plus and minus one standard deviation.

Table 1. Logistic regression explaining knowing about ChatGPT

	b **(*SE*)**	**EXP(*b*) [95% CI]**	**Estimated proportions**	
			At *M* +/- 1 *SD* [a]	**Difference**
Constant	-0.10** (0.32)	0.90		
Age	-0.01* (0.00)	0.99 [0.98, 100]	{0.615, 0.549}	-.066
Female	-0.74*** (0.12)	0.47 [0.38, 0.60]	{0.661, 0.492}	-.169
Low education	-0.31† (0.16)	0.74 [0.54, 1.00]	{0.511, 0.437}	-.074
Higher education	0.92*** (0.14)	2.50 [1.92, 3.26]	{0.511, 0.717}	.207
Conservative–progressive	0.11*** (0.03)	1.12 [1.06, 1.18]	{0.527, 0.635}	.108
Traditional news use	0.19*** (0.04)	1.21 [1.11, 1.32]	{0.529, 0.639}	.116
Social media news use	-0.15 (0.11)	0.86 [0.69, 1.06]	{0.600, 0.564}	-.035
χ^2 (*df*)	209.40*** (10)			
-2 Log likelihood	1715.35			
Nagelkerke R^2	.19			
N	1413			

Note: [a] For the estimated proportions, all scale variables are compared at their means minus and plus one standard deviation. The dummy variables compare simply their categories.
*** $p < .001$; ** $p < .01$; * $p < .05$; † $p < .1$.

As shown in Table 1, we can see that 43.7% of lower-educated individuals were expected to know about ChatGPT, while this was 51.1% for medium-educated and 71.7% for the higher-educated individuals. Non-females (66.1%) had a higher probability of knowing about ChatGPT than females (49.2%), leading to a gap of 16.9 percent points. Respondents who scored one standard deviation above the mean on the conservative–progressive scale and the traditional news use scale had an expected proportion of 63.5% and 63.9% respectively, with respondents one standard deviation below having expected proportions of 52.7% and 52.3%. Not shown in the table, but at two standard deviations from the mean, the predicted proportion even went up to 70.7% (conservative–progressive) and 71.5% (traditional news use), also increasing the gap with respondents two standard deviations below the mean who had expected proportions of 46.2% (conservative–progressive) and 45.4% (traditional news use). This illustrates that these effects are not only significant but also substantial.

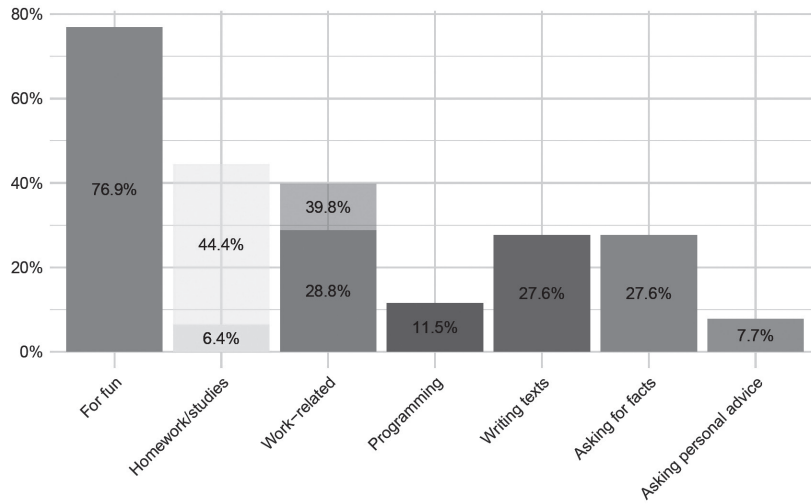

Figure 2. The purpose of ChatGPT use

Purpose of ChatGPT Use

People who used ChatGPT (n = 156) mostly reported having used it simply for fun (76.9%; n = 120). 28.8% (n = 45) of the users also said they used it for work-related tasks. If we solely look at the users who were (self)employed (n = 103), 39.8% (n = 41) indicated they used it for their work (see Figure 2). Interestingly, using ChatGPT for fun was negatively correlated with using ChatGPT for work (r = -.39). Other popular purposes mentioned to use ChatGPT for were writing texts (27.6%; n = 43) and asking for facts (27.6%; n = 43).

Lastly, only 6.4% (n = 10) of the users indicated using ChatGPT for homework or studies. However, if we solely looked at users that were currently in education (n = 18), 44.4% (n = 8) indicated to have used it for their studies. Those who reported having usedit for homework and studies were often also the people who indicated having used ChatGPT to write texts (r = .37).

Perceptions on ChatGPT

On average our respondents seemed to be convinced that ChatGPT will have a moderately large impact on society (M = 4.82, SD = 1.31). When asked whether that impact will be good or bad, they tended to take a more pessimistic view (M = 3.57, SD = 1.34, see Figure 3).

Among the respondents, there was quite some disagreement on how the development of ChatGPT must be perceived (given the relatively high

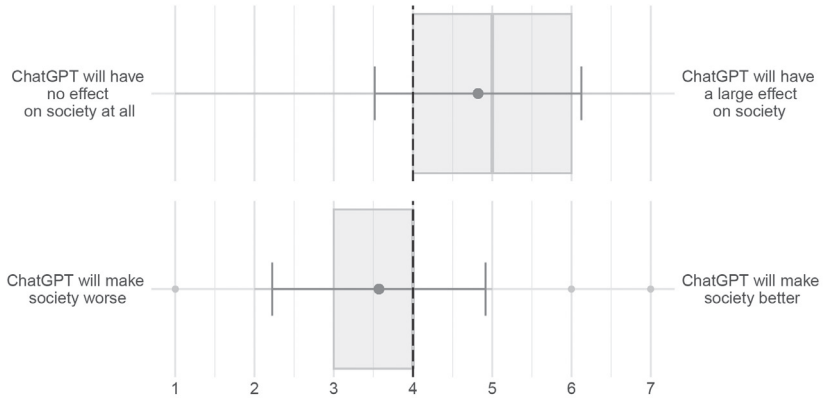

Figure 3. The extent of familiarity with ChatGPT

Note. The red dot represents the mean, with the red line showing the standard deviation. The thick blue vertical line represents the median, the blue block the quartiles.

standard deviations). To give more insights into where this variation comes from, we performed OLS regression analyses with both the perceived size and valence of the impact as dependent variables (see Table 2).

As shown in Table 2, concerning the expected size of the impact of ChatGPT, we found that only age and education seemed to be significant predictors: with age (p = .029), we found that older individuals expected a larger impact on society; with education, it seemed that lower-educated individuals perceived a larger impact on society than individuals who were medium-educated (p = .004) and higher-educated (comparison is not shown in Table 2; difference between lower- and higher-educated: b = 0.43, SE = .15, p = .005). Between medium-educated and higher-educated, we found no significant difference (p = .886).

Regarding the valence of the perceived future impact of ChatGPT on society, it is those who consumed their news through social media that were more positively minded (p = .016). The same could be said for those who had more trust in the government (p = .070) and the higher educated compared to the medium educated (p = .068), but both coefficients did not meet conventional levels of significance. Thus, they at most hint at a potential influence of these two factors but we should be careful to attach strong meaning to this. The most important predictor of the valence, however, was whether someone had used ChatGPT before, with use predicting an increase of 0.67 on the valence scale (p < .001). Adding this predictor also significantly improved the model, increasing the explained variance from .07 to .11.

Table 2. OLS regression predicting size of impact and evaluation of change

	Size of impact			Valence of impact		
	b (se)	***95% CI***	***b****	***b (se)***	***95% CI***	***b****
Constant	4.07*** (0.34)	[3.40, 4.73]	.00	2.55*** (0.34)	[1.89, 3.21]	.00
Age	0.01* (0.00)	[0.00, 0.01]	.09	-0.00 (0.00)	[-0.01, 0.00]	-.06
Female	0.15 (0.10)	[-0.04, 0.34]	.06	-0.05 (0.10)	[-0.24, 0.15]	-.02
Low education	0.44** (0.15)	[0.14, 0.75]	.12	0.11 (0.15)	[-0.20, 0.41]	.03
Higher education	0.02 (0.11)	[-0.20, 0.23]	.01	0.20† (0.11)	[-0.01, 0.41]	.07
Conservative–progressive	0.03 (0.02)	[-0.01, 0.07]	.05	0.04 (0.02)	[-0.01, 0.08]	.06
Traditional news use	-0.00 (0.03)	[-0.07, 0.06]	.00	-0.03 (0.03)	[-0.10, 0.04]	-.03
Social media news use	0.07 (0.09)	[-0.10, 0.24]	.03	0.21* (0.09)	[0.04, 0.39]	.09
Trust in government	-0.00 (0.03)	[-0.06, 0.06]	.00	0.06† (0.03)	[-0.00, 0.12]	.07
Trust in science	0.03 (0.05)	[-0.06, 0.12]	.02	0.07 (0.05)	[-0.02, 0.16]	.06
Trust in Big Tech	-0.06 (0.04)	[-0.13, 0.01]	-.06	0.04 (0.04)	[-0.03, 0.11]	.04
Used GPT	0.20 (0.13)	[-0.05, 0.44]	.06	0.67*** (0.13)	[0.42, 0.91]	.19
F	2.11*			8.19***		
R^2	.03			.11		
N	778			778		

Note: *** $p < .001$; ** $p < .01$; * $p < .05$; † $p < .1$.

Interestingly, traditional media use, although a strong predictor in knowing about ChatGPT, did not significantly predict neither the expected size nor the valence of the impact of ChatGPT. Also, it is remarkable to see that with science and Big Tech, being the main engines behind AI innovations, and with the government, arguably responsible to monitor, channel and perhaps also protect against the impact of AI, the trust in these institutions did not seem to have affected either the expected size or valence of the impact.

Discussion

The aim of this study was to explore which segments of the general public know about, perceive, and use ChatGPT in the early adoption phase shortly after the chatbot became available to the general public. We show that, while around half of our sample had heard of ChatGPT, only a much smaller percentage had used it already. For the people using ChatGPT, the main purpose for usage seems to have been to have fun, with only a few individuals indicating having used it already for tasks that have the potential for a larger impact on society. When asked, participants expected an overall moderate and rather negative impact of ChatGPT on society, however, there were considerable differences between individuals.

ChatGPT as Early Adoption Phase Technology

Awareness-knowledge about a technology, resembling the familiarity with ChatGPT, is seen as the first step of the adoption process (Rogers, 2003). In terms of demographics, we found that being younger, being non-female and being more highly educated predicted knowing about ChatGPT. This resembles previous findings, which showed that early adopters of technologies tend to be male, younger and higher educated individuals (Dedehayir et al., 2017).

Moreover, we found that traditional news media use predicted awareness-knowledge. As there has been much news media attention for ChatGPT, this relationship is not surprising and shows how important traditional news outlets still are for communicating about innovations — also in comparison to social media news use. News about technological innovations can be categorised as a form of metacommunication about innovations which was identified as an important predictor of media adoption (Rogers, 2003; Wirth et al., 2008).

Finally, we found that being progressive was a predictor of ChatGPT awareness. Innovation theories assume that personal beliefs and being cosmopolitan increase technology adoption (e.g., Rogers, 2003). Being progressive might relate to these general traits of open-mindedness towards new developments. Overall, our findings therefore resemble previous assumptions and findings regarding technology adoption, although given that this represents the very first stage of the adoption and appropriation process it remains important to further investigate if these factors also will predict the integration of ChatGPT use in everyday life.

ChatGPT as 'Fun' Technology

When looking at the purpose for which ChatGPT is used, we find that many used it 'for fun'. The possibility to play around with a technology was identified as an important factor in technology adoption research and conceptualized as 'perceived playfulness' (Moon & Kim, 2001; Sledgianowski & Kulviwat, 2009) or as 'trialability' (Al-Gahtani, 2003; Rogers, 2003). While this playing around may thus seem at first as an indication that ChatGPT use represents rather play than substantial society-changing use, one should not underestimate the importance of this playful experimentation for adoption for more substantial tasks.

The percentage of users who already used ChatGPT for work shows that compared to other recent technology innovations, such as social media or smartphones, ChatGPT is much more strongly tied to the workplace compared to private everyday life. Still, it seems noteworthy that a small percentage of users have already used it to find answers to personal questions and to find facts. This seems especially important, considering that ChatGPT was shown to be particularly inaccurate when it comes to facts (e.g., Pearl, 2022). Getting more insights about how trustworthy users evaluate the answers to fact-based questions and with what aims users ask for facts and personal questions is, therefore, an important aim for future research and observation.

ChatGPT as Adverse Technology for Society

Finally, we found that, overall, the expected impact on society by ChatGPT was negative, meaning that, generally, individuals expect society to become worse as a result of ChatGPT. Among individuals who have used ChatGPT before, and among social media news users, however, the expected impact was more positive. Previous research has shown that experience with technologies leads to a more positive evaluation of these technologies (e.g., Varma & Marler, 2013). This could be called a technology contact hypothesis that proposes that experience with new technologies might reduce anxiety and concerns around these technologies. This hypothesis might contribute to the literature on moral technology panics (Marwick, 2008; Orben, 2020).

Regarding the effect of social media news usage, social media might be a proxy for a general optimism towards technology and on the other side, not using social media news might be more the norm among technology pessimists (e.g., Kerschner & Ehlers, 2016). Another explanation would be that news on social media paints a more positive picture of ChatGPT.

Traditional media news use, in comparison, did not have an impact on the positive–negative evaluation. Content analyses of both traditional and social media news sources might be interesting to determine if the framing differs between different news outlets.

Surprisingly, trust in various institutions did not predict a positive or negative evaluation of ChatGPT. Given that ChatGPT is financed by Big Tech companies such as Microsoft, we expected that trust in these companies would be related to the evaluation of this technology. A potential explanation for not finding this relationship might be that the connection between ChatGPT and Big Tech companies was not clear in the Dutch public yet at the time of the data collection. Observing how this relationship develops over time is an interesting focus for future research.

Regarding the perceived size of the impact of ChatGPT on society, we found large differences between individuals. Notably, the predictors examined in this study explained very little of these differences. This could indicate that people have not yet formed firm judgments, but that the responses represent uncertain and unstable evaluations. It is also possible that we did not capture relevant influencing factors. One possible important predictor could be basic technology affinity or literacy. Future research, which might then observe a crystallisation of views (Howe & Krosnick, 2017) would therefore be particularly valuable.

Limitations

While our study provides interesting insights into the emerging use of ChatGPT at an early stage of the adoption process, our study comes with limitations. We recruited a large sample drawn such that it would match the Dutch population in age, gender and education. However, our final sample did not entirely match the demographic distribution of the Dutch population. Moreover, the distribution of an online survey might have excluded parts of society that are the least online. Thus, our sample might not be entirely representative of the Dutch population. In addition, it is important to acknowledge that the present findings only depict a snapshot of the ChatGPT adopting process and usage as well as perceptions of ChatGPT might be quickly changing.

Concluding Remarks

To conclude, our data provide insights into who knew and used ChatGPT and how ChatGPT's potential influence on society was evaluated in Dutch society

in the very early adoption phase. We see that many of the factors explaining awareness and use can be connected to the literature on the diffusion of innovations and technology. For further adoption and use as well as the evaluation of ChatGPT it might be particularly interesting to look at metacommunication processes through traditional and social media news sources and assess how the public media discourse shapes the views of individual users. Moreover, our results suggest that using ChatGPT might be connected to a more positive evaluation of its impact on society. Our results provide a first valuable anchor point that can be fruitfully used as a comparison point for future studies on the usage and the viewpoints on ChatGPT.

Notes

1. We asked ChatGPT to propose a title for our paper. It came up with: 'Unlocking Dutch Minds: A Fascinating Journey into ChatGPT Adoption and Attitudes.' As this title did not fit that well with the paper, we chose to go with our own title.
2. The counts do not add up, because the exclusion criteria are not mutually exclusive.
3. For reasons of clarity we present here the logistic regression with the three categories in which the respondent knew about ChatGPT merged, creating a knowledge of ChatGPT dichotomy. As a check, we also ran a multinomial logistic regression analysis with the original variable, which led to generally the same conclusions. Notable differences are: [1] Age primarily predicts using ChatGPT, not the difference between knowing and not knowing about ChatGPT. [2] Those who are medium educated often know more about ChatGPT than the lower educated, but they do not use it more often; it's the higher educated that use ChatGPT more often than both lower and medium educated. [3] News exposure predicts whether a respondent know about ChatGPT, not whether they used it. [4] Individuals who get news from social media know less often about ChatGPT, but the regular users of ChatGPT are also the highest social media news users.

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