DISSERTATION

Exploring the adoption of symptom-assessment applications in Germany: An investigation of awareness, use, and usefulness

Die Verbreitung von Symptom Checker Anwendungen in Deutschland: Eine Untersuchung zur Bekanntheit, Nutzung und Nützlichkeit

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AI = Artificial Intelligence

Delta (Δ) = Difference in means/proportions

DiGa = digitale Gesundheitsanwendung(en) (health apps covered by health insurance)

ePA = elektronische Patientenakte (electronic health record)

M = Mean

n = Number of

OR = Odd’s Ratio

r = Correlation coefficient

SAA = Symptom Assessment Application

SD = Standard deviation

UK = United Kingdom

US = United States

Abstract

Background: Symptom-assessment applications (SAAs) allow laypeople to obtain advice on whether and where they should seek medical care, along with possible diagnoses. Although their average accuracy is currently far from perfect, SAAs might in fact have the potential to unburden healthcare systems. Previous studies from the United States and the United Kingdom indicate that users of these systems are mostly young, female, and well-educated. However, data on SAA awareness in Germany is scant. Thus, this thesis aims to assess the extent of awareness, use and perceived usefulness of SAAs in a German sample and to explore how different respondent characteristics are associated with them.

Methods: We conducted a cross-sectional online survey, with 1,084 German respondents stratified to reflect the German population. They were asked several questions involving individual characteristics, as well as questions about their knowledge and use of SAAs and their perception of SAA usefulness. The collected data were analyzed exploratively.

Results: Respondent awareness of SAAs was 16.3% and respondent rate of using SAAs 6.5%. Among those who were aware of SAAs, 40.1% had used them. Of those, 40.8% considered SAAs useful. Users were on average younger ($M = 37.6$, $SD = 14.3$) than nonusers ($M = 47.3$, $SD = 15.8$), more often female (62.0% among users vs. 50.9% among nonusers), and well educated (42.3% with a university or college degree vs. 27.6%). Similar characteristics were observed for those who were aware of SAAs. However, these characteristics did not differ between users and respondents who were aware of SAAs but did not use them. Knowing about the existence of SAAs was associated with the use of other eHealth applications ($r = .23$) and knowing about digitale Gesundheitsanwendungen (DiGA) ($r = .13$) and the elektronische Patientenakte (ePA) ($r = .11$). Using SAAs was associated with using other health apps ($r = .25$), DiGA ($r = .19$) and ePA ($r = .22$), but not with being aware of these applications ($r = -.05$ and $r = -.08$, respectively).

Discussion: The data from our study suggests a slightly lower number of SAA users in Germany—yet at the same time twice as many respondents who were aware of the existence of SAAs—than a previous study did. We replicated results from previous studies (that found users to be younger, more often female, and well educated) and extended these findings by showing that these characteristics are associated with awareness of

SAAs but not with SAA use itself. The data also indicates the existence of two separate concepts regarding eHealth technologies: Knowing about these technologies and using them. This difference should be considered in future studies when interpreting data on characteristics of SAA and eHealth users. Ultimately, to maximize SAA potential and its ability to support the public, approaches should be devised that would reach those who might benefit from the technologies but who are currently unaware of their existence.

Zusammenfassung

Hintergrund: Symptom-Assessment Applications (SAAs) geben Laien Empfehlungen, ob und wo sie medizinische Hilfe aufsuchen sollten—begleitet von möglichen Diagnosen. Obwohl die Genauigkeit im Durchschnitt mittelmäßig ist, könnten sie Gesundheitssysteme entlasten. Vorherige Studien aus den USA und Großbritannien zeigen, dass Nutzer*innen meist jung, weiblich und hoch gebildet sind. Daten zur Bekanntheit von SAAs fehlen allerdings; besonders für Deutschland liegen kaum Daten vor. Das Ziel dieser Arbeit bestand darin, die Bekanntheit, die Nutzung und die wahrgenommene Nützlichkeit von SAAs in Deutschland zu untersuchen und den Einfluss diverser Charakteristiken auf diese Faktoren zu analysieren.

Methoden: In einer Querschnittsbefragung wurden 1.084 Personen aus Deutschland—stratifiziert, um der deutschen Bevölkerung zu entsprechen—befragt. Sie wurden zu verschiedenen Charakteristika, sowie zur Bekanntheit, Nutzung und wahrgenommenen Nützlichkeit von SAAs befragt. Die Daten wurden explorativ ausgewertet.

Ergebnisse: Unter den Befragten kannten 16,3% SAAs und 6,5% nutzten sie. Unter Nutzer*innen hielten sie 40,8% für nützlich. Die Nutzer*innen waren im Durchschnitt jünger ($M = 37{,}6$, $SD = 14{,}3$) als Nichtnutzer*innen ($M = 47{,}3$, $SD = 15{,}8$), häufiger weiblich (62,0% der Nutzer*innen gegenüber 50,9% der Nichtnutzer*innen) und hatten ein höheres Bildungsniveau (42,3% mit Universitäts- oder Hochschulabschluss gegenüber 27,6%). Ähnliche Merkmale wurden bei Personen beobachtet, die SAAs kannten, aber nicht unter Nutzer*innen, wenn sie mit Nichtnutzer*innen, die SAAs kannten, verglichen wurden. Die Bekanntheit von SAAs korrelierte mit der Nutzung anderer eHealth-Anwendungen ($r = .23$), der Bekanntheit von digitalen Gesundheitsanwendungen (DiGA) ($r = .13$) und der elektronischen Patientenakte (ePA) ($r = .11$). Die Nutzung von SAAs korrelierte mit der Nutzung anderer Gesundheitsanwendungen ($r = .25$), DiGA ($r = .19$) und der ePA ($r = .22$), aber nicht mit der Kenntnis dieser Anwendungen ($r = -.05$ bzw. $r = -.08$).

Diskussion: Die erhobenen Daten zeigen einen etwas niedrigeren Anteil an SAA Nutzer*innen—aber doppelt so viele Personen, die SAAs kennen—als eine frühere Erhebung in Deutschland. Die Ergebnisse aus früheren Studien (dass Nutzer*innen eher jünger, häufiger weiblich und höher gebildet sind) konnten repliziert werden. Diese Ergebnisse wurden erweitert, indem wir zeigen konnten, dass die Merkmale nicht direkt mit der Nutzung, sondern mit der Bekanntheit von SAAs assoziiert sind. Unser Daten deuten außerdem daraufhin, dass es bei der Nutzung von eHealth-Technologien im Allgemeinen zwei Faktoren geben könnte: Die Kenntnis von Technologien und die Nutzung dieser. Dieser Unterschied sollte bei der Interpretation von zukünftigen Studien zu Charakteristiken von Nutzer*innen berücksichtigt werden. Um das Potenzial von SAAs auszuschöpfen, sollten Strategien entwickelt werden, mit denen Personen angesprochen werden, die von SAAs profitieren könnten, sie aber noch nicht kennen.

1 Introduction

1.1 Introduction

As healthcare systems become more digitalized, both prevention and care are becoming more efficient (1,2). But the digitalization of healthcare systems is accompanied by a growing amount of data that needs not only to be generated but also to be analyzed. Open data and open-source software are more accessible to everyone and allow for the development of solutions for several use cases. For example, they can be used for disease prediction, better insights into the lives of people with chronic diseases, and improved clinical decision-making (3,4); an exemplary development in this latter area is a clinical decision-support system. And even though some of these systems have been around for a relatively long time—some already available as far back as 1972 (5)—further advances in data generation, availability, computational power, and analysis techniques have enabled these systems to tackle even more challenging and complex tasks and at the same time have made them easier to use (6).

These clinical decision-support systems are typically aimed at medical professionals, but information is becoming more available for patients as well. As a result, patients could be better informed and their participation in clinical decision-making could be increased. Yet though, with the internet, users have nearly all the information they could ever desire at their fingertips, that includes some information that would require medical expertise to interpret. There are several ways to structure (health) information online: Government websites, search engines, chatbots with large language models, dedicated eHealth applications, and also social media. But despite the benefits of these various sources, they also carry risks, such as misinformation or increased health-related anxiety (known as "cyberchondria" (7)) due to the nearly unfiltered and hard-to-interpret floods of information that are available. In other words, the internet can be a great tool for general information, but it might not be as useful for self-diagnosis. Although patients should be involved in clinical decision-making and informed patients are associated with better outcomes (8), it needs to be a professional who makes the final diagnosis. The internet can, however, assist patients in deciding when they need to see a healthcare professional and how urgent that need is. There have been few studies about care-seeking decisions, but the industry is already providing several different solutions to assist patients.

1.2 Patients' self-triage decision-making and information seeking

Most patients choose where to seek care based on their own knowledge or with the help of the internet (9). With no assistance, they don't make the best decisions, with only 61% of those decisions being correct (10). Most errors seem to be over-triage errors (i.e., judged to be more urgent than they actually are) which suggests a tendency towards risk-averse care decisions (10–12). When analyzing these decisions in more depth, we found—in line with another study by Mills et al. (12)—that patients face specific difficulties in distinguishing between emergencies and cases in which they could either treat themselves or wait for treatment (13). Despite the tendency toward error in their decisions, though, the patients in that study were very confident in all of their decisions (13).

However, when patients feel that their own knowledge is insufficient, they experience a so-called informational need (14) and seek to obtain new health information. A common approach for such a search is to make use of the internet, since it is a source of easily accessible, detailed information that can be accessed quickly (15,16). To search for health information online, most people use search engines (9). On the one hand, this allows them to learn about possible diagnoses and treatment options, and to locate local health care providers. On the other hand, despite being commonly used, search engines seem limited in displaying accurate health information when non-medical terms are entered, which is how many laypeople frame their search questions (17). Additionally, their algorithms rank results not on the most accurate information, but on popularity—which could lead to misinformation and give participants a belief of being well-informed even though they are relying on potentially inaccurate information (18,19). In fact, a majority of users seem confident in decisions that they make with the help of search engines—even if they are in fact relying on incorrect advice (20). This is to be expected in such searches, as information processing is subject to certain biases, and actively searching for information can reinforce these biases: A typical example occurs with the anchoring bias, in which an information search is based on the first information found, and further information is sought based on that information. Despite these drawbacks, search engines are widely used, with an estimated 50% to 71% of Americans and Germans using search engines to obtain health information (21). In 2020, around 20% of Germans actually stated that they obtained most of their health information online (22).

Although the internet and search engines can provide patients with valuable information, these limitations illustrate the diverse challenges associated with their use. For that reason, dedicated eHealth products are being developed for different application scenarios. Symptom assessment applications (SAAs) have been created specifically to help with care-seeking and self-diagnosis decisions.

1.3 Symptom assessment applications (SAAs)

SAAs (sometimes called “symptom checkers”) can be defined as “smartphone- or web-based applications for laypersons providing an individualized assessment of the entered health complaints by providing suggestions on likely diagnoses and a categorization of their treatment urgency” (23, p. 2) and are typically operated by users for themselves or by a user trying to assess symptoms for others. It has been argued that “triage advice” (where and how urgently to seek care) is the more important function since a final diagnosis will be made by a specialist anyway (24). The advice given by SAAs is produced using different algorithms: Some use Bayesian networks, some use recurrent neural networks, and others use simple rule-based algorithms (25–28). Although it might be assumed that more complex models (i.e., based on “Artificial Intelligence” (AI)) perform better, this does not seem to be the case. In a direct comparison, AI-based SAAs did not have a substantially higher accuracy rate than rule-based SAAs (29). Another factor that might influence performance is the number of questions asked, as some SAAs provide an assessment very quickly and pose only a few questions to the user, while others take several minutes to present more detailed questions. An analysis of the number of questions presented found that SAAs asking more questions gave more accurate advice, but the correlation was not strong (30).

1.4 Accuracy of SAAs

In general, accuracy has been tested in various studies and in fact represents the most-studied aspect of SAA research. Accuracy has mostly been tested using case vignettes—descriptions of patients derived from either educational resources and text books (24,29,31) or from real patient cases (32,33). Despite its methodological limitations such as questionable ecological validity (34), this method is currently the gold standard for evaluating SAA accuracy. The first study of SAA accuracy was conducted by Semigran et al. in 2015 (24); it found an average accuracy of 34% for diagnoses and 80% for triage advice. Subsequently, there have been numerous other studies conducted to assess SAA accuracy from both independent researchers (24,29,35) and SAA developers (36,37). Some have even compared SAAs to general practitioners, ascertaining a similar triage performance between the two, but at the same time an inferior diagnostic performance by the SAA (37–39). According to a recent meta-analysis, SAA diagnostic (primary diagnosis) performance today ranges from 19-38% and triage performance from 49-90% (40). With technological advances, it is conceivable that accuracy might improve over time—however, a previous study from our research group did not find evidence for that hypothesis (35). When tested with the same case vignettes after 5 years, the same SAAs showed no improvement in accuracy, although they did become less risk-averse. In summary, most studies suggest that SAA accuracy is in general far from perfect, but that performance varies widely, with some apps performing very well.

1.5 SAA use and effects

Even with their tendency to a lower average accuracy, the use of SAAs (especially well-performing SAAs) might have positive consequences. Most specifically, they could guide individuals toward the most appropriate care facility, saving both time and money (24,41). Furthermore, not having to refer patients to other locations could free up additional resources in the healthcare system. Overall positive effects of SAAs, however, can only be realized when users make better decisions *with* SAAs than they do without them. In a comparison with medical laypeople, SAAs have a similar accuracy rate but are better at detecting emergencies than laypeople are (10). Their risk-averse design, however, leads them to classify some cases as unnecessarily requiring emergency care, which could end up increasing emergency department overcrowding rather than reducing it. According to a study on telephone triage (as a comparable system), healthcare burdens were redistributed, not reduced (42), whereas a study of pediatric SAAs failed to find evidence of a reduced number of visits to the emergency department (43). In contrast, introducing an evidence-based health information website in the Netherlands resulted in a 12% reduction in healthcare utilization (44). It remains unclear whether SAA use leads to any observable benefits or harms at present.

In a study of telephone triage hotlines, Roivainen et al. found that most callers were satisfied with receiving medical advice without treatment (45). SAAs could provide this advice without requiring direct communication with a healthcare provider, which could free up resources. In terms of following received advice, we found in a lab study that most people intend to follow the advice they receive from an SAA (46). Results from three prospective observational studies support this finding (47–49). One of these studies examined 158,083 SAA encounters and asked users about their care-seeking intent before and after the encounter (49); in more than a quarter of the cases, respondents felt a decreased level of urgency. Similar results were found in a study focusing on a primary care clinic, where 13% of participants indicated that the SAA would have reduced their perceived urgency level (50). The intent to follow advice might be a biased measure for assessing behavior (as intentions are not always followed by actual behavior, an observation called intention-behavior gap (51)), but another retrospective observational study assessed actual behavior after an SAA was used, and found that more than half of respondents followed the SAA advice (52). Thus, most people seem not only to intend to follow the received advice, but also do follow it.

Patients generally seem to overestimate how urgent their symptoms are, but previous studies suggest that—despite the fact that SAAs are typically designed to be risk-averse (53)—many users actually reduce their urgency perception after using SAAs, and that they follow the recommendations that they receive from the SAA. While there are no recent studies specifically looking at SAAs' impact on healthcare systems, the studies cited here suggest that SAA use could reduce patient demands on healthcare systems—even though SAAs are designed to be risk-averse.

1.6 Individual characteristics associated with SAA use

To maximize these potential benefits, SAA design should both match the characteristics of users and be tailored to their needs. Women, for instance, were found to be more risk-averse than men (13,54), which is important to take into account when assessing the effects of following SAA recommendations and in considering emergency department overcrowding.

To date, several studies have assessed characteristics that are associated with using SAAs or benefiting from them. A study from the US surveyed users of the SAA Buoy Health and found them to be relatively young on average, more often female (85%) and well-educated (47). Users rated the SAA as useful in general, but no individual characteristics associated with perceived usefulness were reported by the authors. Another study surveyed Buoy users as well and found similar characteristics: Users were young and most often female (78%) (49). A third study from the US surveyed users of Isabel (55): In line with the other studies, users were generally young, more often female (76%), and had higher levels of formal education. Again, most users reported considering the SAA useful, but the authors did not report any of the characteristics associated with finding it useful.

In a study conducted in the UK, patients visiting a primary care clinic were given the SAA Ada (50). They found—similarly to studies involving established users—that those willing to participate were more often young and female (62%). They also assessed usefulness and concluded that younger participants found the SAA to be more useful than older participants did, but they did not find any gender differences. In a similar study from Germany, the authors gave two different SAAs to patients visiting rheumatology outpatient clinics (56). Although age was not associated with participation in this instance (presumably because of the sampling method), participants were once again more often female (70%). Generally, SAAs were considered useful, but in this study, older patients found them to be more helpful than younger patients did.

In summary, SAA users appear to be younger, more often female and to have higher levels of formal education (57). While some studies report high levels of perceived usefulness, only a few examined characteristics associated with that. The two studies that reported age as an influential characteristic reached opposing conclusions.

1.7 Aim of this thesis

A vast body of research already exists on the accuracy of SAAs and how they might affect decision-making. For SAAs to be truly effective, however, individual characteristics must be taken into account. First studies have shown that users might differ from the general population and have specific characteristics (e.g., they are generally younger and female). Despite initial user characteristics described in these studies and estimations of the overall number of users from market research institutes, not much data is available on general awareness of SAAs. That data would be relevant, however, as factors related to use might not be associated with willingness to use SAAs themselves, but rather with awareness of their existence. Results of a qualitative study indicate that few people are aware of SAAs (58), but reliable estimates of those numbers are lacking. Moreover, few studies have examined the individual characteristics associated with perceived usefulness—and those studies that have have come to different conclusions. Furthermore, there is a lack of studies specific to Germany comparable to those from the US. A recent report estimates the proportion of SAA users in the German population to be 13% (59), but it has not reported characteristics found in other SAA user studies. This thesis attempts to fill these research gaps. My primary goal in this study has been to assess the degree of awareness, use, and perceived usefulness of SAAs. The secondary objective was to exploratively examine the individual characteristics associated with awareness, use, and perceived usefulness of SAAs in a German sample.

2 Methods

A full description of the methods used in this study can be found in Kopka et al. (60). In this section, I will summarize the main components of our methods and outline the reasons for our choices.

2.1 Study Design

This study was designed as a cross-sectional survey (with an exploratory data analysis) of the general public as that method is best suited to determining point prevalence (in this case the rates of awareness, use, and perceived usefulness of SAAs) (61). Since a control group is not necessary to determine prevalence, we did not use a specific control group. However, we also explored individual characteristics associated with awareness, use, and usefulness of SAAs and compared (a) those aware of SAAs to those not aware, (b) those using SAAs to those not using SAAs, (c) those using SAAs to those aware of but not using SAAs, and (d) those considering SAAs useful to those not considering them useful. Thus, our control groups in these exploratory analyses can be viewed as respondents (a) unaware of SAAs, (b) not using SAAs, (c) not using SAAs but aware of them, and (d) considering SAAs not useful. Because the groups were dichotomous or dichotomized (e.g., to respondents aware of SAAs and those not aware of them), these control groups are independent from the corresponding exposure group and allow (descriptive) comparisons.

2.2 Participants

The respondents were recruited using the market research company bilendi/respondi, which used a stratified random sampling (to reflect the German population with regard to age, gender, income, and federal state) of their user base. In accordance with the budget available, we sought to collect data from at least 1,000 respondents. Although not based on an a priori power analysis, we deemed this sample size sufficient as several other studies examining the rate of eHealth use used similar sample sizes (62–65). The inclusion criteria were being at least 18 years old and giving informed consent. Respondents were paid 1€ for their participation as outlined by bilendi/respondi’s guidelines.

Overall, 1,555 people opened the survey, 400 did not complete it, and four participants were screened out. We embedded control questions (such as "Please select 'Completely disagree'") to increase data quality (i.e., so that we could exclude participants who did not participate attentively). 67 participants were excluded for not answering these control questions correctly. Hence, data from 1,084 respondents were included in our analysis.

2.3 Survey Instruments

The primary outcome of our study was the point prevalence of SAA awareness, use, and perceived usefulness among participants. Secondary outcomes included several individual characteristics of participants (see Table 1). These characteristics were explored in order to generate hypotheses about potential differences between subgroups (listed in 2.1). We asked respondents questions about mental health disorders for which DiGA (Digitale Gesundheitsanwendungen, official health apps paid for by health insurance) are available, as mental health has only rarely been considered in SAA research as of yet but is nevertheless a part of the German healthcare system. Furthermore—to explore the association between awareness/use of SAA and that of other eHealth applications—we included questions about eHealth technologies that are available in Germany: DiGA and ePA (elektronische Patientenakte, electronic health record). In addition, we asked respondents what functions they use health apps for in order to gain a more comprehensive understanding of differences in general health app use.

The survey was administered online, in the German language, and included four sections about (a) sociodemographic variables, (b) health variables, (c) technology and health apps usage, and (d) questions about SAAs. Table 1 summarizes the measured variables, the operationalization of corresponding survey instruments, their type of measurement, and quality criteria. All validated instruments (i.e., complete questionnaires, not single questions answered) satisfied the common survey instrument quality criteria.

Table 1: Collected variables with survey instruments used and their type of measurement and quality criteria.

Variable	Survey Instrument	Type of Measurement	Quality Criteria in Instrument Validation
Age	How old are they	numerical text field	not applicable
Gender	With what gender do they identify	Male/Female/ Diverse	not applicable
Education	Questions based on the SES-Index (66)	Choice of 1 out of 6 options	not applicable
Net household in-come	Questions based on the SES-Index (66)	numerical text field	not applicable
Municipality size	Question as articulated by the Federal Statisti-cal Office (with fewer categories because the granularity was not necessary) (67)	Choice of 1 out of 7 options	not applicable
Migration back-ground	Question as articulated by the Federal Statisti-cal Office (68)	yes / no	not applicable
Native German speaker	Is German their native language	yes/no	not applicable
Self-efficacy	Allgemeine Selbstwirk-samkeit Kurzskala / Self-Efficacy Scale – Short (69)	5-point Likert scale	Reliability: ω > .81, Re-test-Reliability = .50 Validity: content-, facto-rial-, convergent, discri-minant- and predictive validity acceptable
General health	WHO Minimum Euro-pean Health Module (70)	Choice of 1 out of 5 options	Reliability: κ > .73, Validity: not assessed
Restrictions for health reasons	WHO Minimum Euro-pean Health Module (70)	Choice of 1 out of 3 options	Reliability: κ > .73, Validity: not assessed
Chronic disease	WHO Minimum Euro-pean Health Module (70)	yes/no	Reliability: κ > .73, Validity: not assessed
Depression	Have they been diag-nosed with depression before	Checked all that applied	not applicable
Panic- or anxiety disorder	Have they been diag-nosed with panic- or anxiety disorder before	Checked all that applied	not applicable

Variable	Survey Instrument	Type of Measurement	Quality Criteria in Instrument Validation
Chronic pain	Have they been diagnosed with chronic pain before	Checked all that applied	not applicable
Type of health insurance	What type of health insurance do they have	Choice of 1 out of 4 options	not applicable
Permanent primary care physician	Do they have a permanent primary care physician	yes/no	not applicable
Number of physician visits in the last year	How often have they visited a physician in the last year, based on Link et al. (16)	numerical text field	not applicable
Currently in psychotherapy	Are they currently in psychotherapy	yes/no	not applicable
Inpatient hospital stay in the last year	Were they hospitalized in the last year, based on Link et al. (16)	yes/no	not applicable
Frequency of internet use	How often have they used the internet, inspired by Fergus & Dolan (71)	Choice of 1 out of 5 options	not applicable
Affinity for technology	Affinity for Technology Interaction Scale (72)	6-point Likert scale	Reliability: α > .83 Validity: construct validity acceptable
General health app usage	Had they generally used a health app before	yes/no	not applicable
Awareness of SAAs	Did they know of SAAs (after a description)	yes/no	not applicable
Use of SAAs	Had they used an SAA before	yes/no	not applicable
Perceived usefulness of SAAs	Usefulness question based on Knitza et al. (56)	5-point Likert-type single question	not applicable
Awareness of DiGA	Did they know of DiGA (after a description)	yes/no	not applicable
Use of DiGA	Had they used a DiGA before	yes/no	not applicable
Awareness of ePA	Did they know of the ePA (after a description)	yes/no	not applicable
Use of ePA	Had they used the ePA before	yes/no	not applicable

Variable	Survey Instrument	Type of Measurement	Quality Criteria in Instrument Validation
Functions of health apps used	Had they used an app for one or multiple of 7 functions before	Choice of 7 possible functions, yes/no	not applicable

Note: The exact answer options of multinomial variables are presented in the supplementary material of Kopka et al. (60)

2.4 Data Analysis

We conducted exploratory analyses with an alpha level of .05 and corrected for multiple testing with the Benjamini-Hochberg procedure as a robustness check. Further, we excluded the top and bottom 2.5% income values as outliers because these data were considered implausible after inspection. Since the analysis was exploratory, all results and p-values should be interpreted as hypothesis-generating, not as hypothesis-testing.

In the publication, we focused on four comparisons: (a) those aware of SAAs with those unaware of them, (b) those using SAAs with those not using SAAs, (c) those using SAAs with those aware of but not using SAAs, and (d) those considering SAAs useful to those considering them unuseful. For the last comparison, we grouped those considering SAAs “Completely unuseful” or “Somewhat unuseful” into “Unuseful” and those considering them “Somewhat useful” or “Very useful” into “Useful”. The exact analysis is described in Kopka et al. (60). As a measure of differences between means and proportions, I will report Δ. Furthermore, I will use an alluvial plot as a visualization of the rate of awareness, use, and perceived usefulness of SAAs, and plots inspired by forest plots as a visualization of the differences in characteristics.

In addition to what appears in Kopka et al. (60), I will present two analyses of SAA awareness and willingness to use, comparing them with other eHealth technologies (such as DiGA and ePA).

I will examine only willingness to use, not general use, since only this subset of respondents can make an informed decision to (not) use SAAs. Comparing users with the whole sample is not as important for this comparison since user awareness of SAAs would be a confounding variable when examining SAA use.

First, the correlations of SAA awareness, willingness to use, and usefulness with being generally aware of health apps, and with being aware of or using DiGA and ePA will be reported. These correlations were assessed using the Phi correlation coefficient for binary data and the Glass rank biserial correlation coefficient for ordinal data (usefulness). For a better understanding of quantitative differences, absolute numbers and proportions with confidence intervals will be presented next. The effect sizes (as in the publication) will not be reported since they are identical to the correlations. Inferential statistics were conducted using Chi-square tests. Second, we asked participants what functions they generally use in health apps and compared these different functions between users and non-users (aware of SAAs) using Chi-square tests as well as a visualization of the proportions in a forest plot.

The data were analyzed using R (version 4.1.2) (73). In addition to the packages used for the main analyses, I used ggalluvial (74) for data visualization and rcompanion (75) to calculate the Glass rank biserial correlation coefficient.

3. Results

In section 3.1, I will give an overview of the results published in Kopka et al. (60) and summarize the key findings. The first part will provide descriptive statistics on the awareness, use, and usefulness of SAAs. The second part will compare characteristics discovered in previous studies between people who (a) know of SAAs vs. don't know of them, (b) use SAAs vs. don't use them (c) use SAAs vs. know of them but don't use them (c) found SAAs useful vs. did not find them useful. The characteristics examined are age, gender (the proportion of female users), education, and affinity for technology. The third part will compare influential characteristics—that we exploratively discovered in our study—between these user groups.

In section 3.2, I will present additional analyses—not published in Kopka et al. (60)—of the data on the relationship between awareness and use of SAAs and awareness and use of other eHealth applications. The first part will focus on the association of SAA awareness, use, and usefulness with other health apps in general and two specific eHealth technologies available in Germany: Health apps that are covered by health insurance (DiGA) and electronic health records (ePA). In the second part of this section, I will explore how SAA users' health app function use differs from that of nonusers.

3.1 Overview of results from Kopka et al. (60)

The study included data from 1,084 individuals. 16.3% (177/1084) reported having heard about SAAs and 6.5% (71/1084) had used SAAs. Of those who had heard about SAAs, 40.1% (71/177) had used them before. 21.1% (15/71) of users had found them very useful, 19.7% (14/71) had found SAAs somewhat useful, 33.8% (24/71) had found them to be sometimes useful, sometimes not, 19.7% (14/71) had found them somewhat unuseful, and 5.6% (4/71) had found them not useful at all. These proportions are laid out in Figure 1.

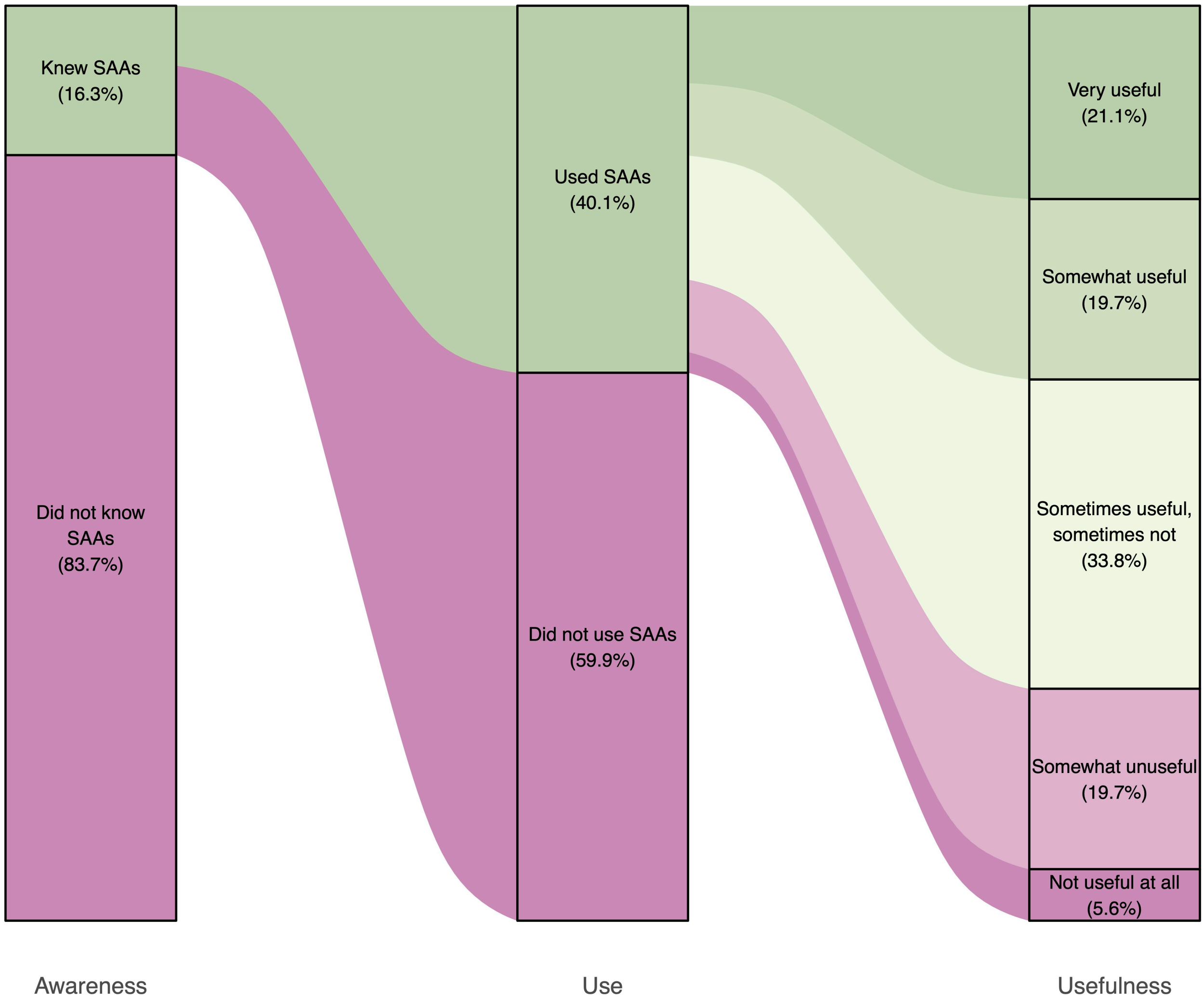

Figure 1: Proportions of respondents' SAA awareness, use, and usefulness ratings; figure based on data from Kopka et al. (60), own representation.

There was a statistically significant age difference (Δ_M = 9.5 years, p <.001) between respondents who were aware of SAAs and respondents who were not. This difference persists when distinguishing between users and nonusers (Δ_M = 9.7 years, p < .001). However, we did not find a statistically significant age difference between SAA users and nonusers who knew about SAAs (Δ_M = 2.0 years, p = .380), nor did we find any significant difference between respondents who rated them (somewhat) useful and respondents who rated them (somewhat) unuseful (Δ_M = 0.7 years, p = .882).

The proportion of women among those who were aware of SAAs was higher than among those who were not aware of SAAs (Δ = 10.6 percentage points, p < .001). Likewise, this difference exists when SAA users are compared to nonusers (Δ = 11.0 percentage points, p = .028), but it was not observed when SAA users were compared to nonusers who were aware of SAAs (Δ = 2.6 percentage points, p = .426). Among those who found SAAs (somewhat) useful, women accounted for a smaller proportion of the whole than they did among those who found SAAs (somewhat) unuseful (Δ = 27.4 percentage points, p = .009).

A similar pattern emerged for education level: There was a statistically significant difference among people with a tertiary degree between those who knew of SAAs and those who did not (Δ = 14.5 percentage points, $p < .001$), and this difference also existed when comparing users and nonusers (Δ = 14.6 percentage points, p = .008). Again, this difference was not observed when comparing SAA users and nonusers who were aware of SAAs (Δ = 2.7 percentage points, p = .727). However, there were more people with tertiary degrees among those who considered SAAs (somewhat) useful than among those who did not (Δ = 33.0 percentage points, p = .026).

Affinity for technology follows this trend as well: We observed statistically significant differences in technology affinity between those who were aware of SAAs and those who were not ($\Delta_M = 0.51$ on a scale of 1 to 6, $p < .001$), as well as between users and nonusers ($\Delta_M = 0.41$, $p < .001$). This difference was not observed—in line with the proportional results regarding women and those with a tertiary degree—when comparing SAA users and nonusers aware of their existence ($\Delta_M = 0.06$, p = .627). On average, those who rated SAAs as (somewhat) useful had a higher technology affinity than those who rated them (somewhat) unuseful—but this difference did not reach statistical significance ($\Delta_M = 0.35$, p = .233).

A visual summary of these results can be found in Figure 2.

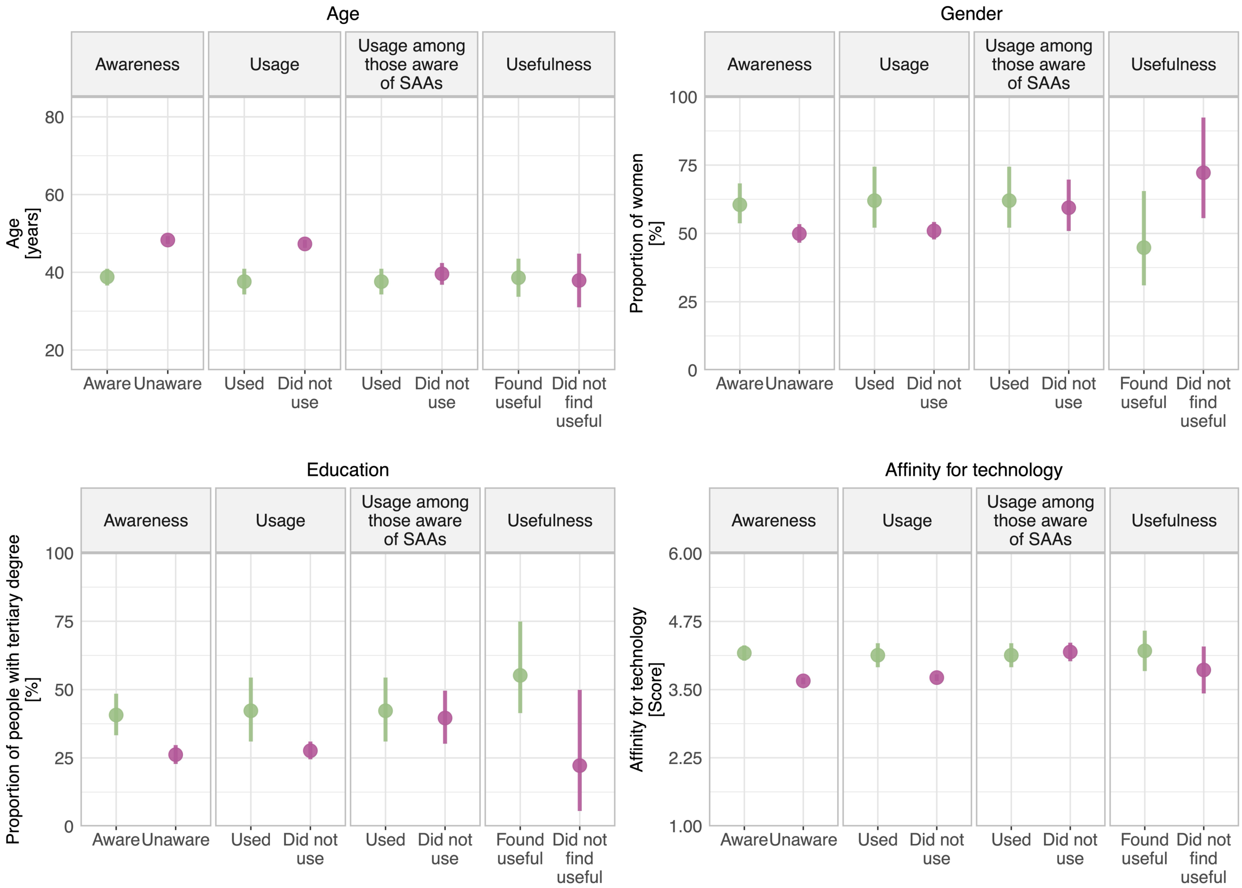

Figure 2: Comparison of age, gender, education, and affinity for technology among different reference groups; figures based on data from Kopka et al. (60), own representation.

Note: Previous studies found a high proportion of women and higher formal levels of education (tertiary degrees) among SAA users. For this reason, the proportion of women and the proportion of respondents with a tertiary degree are presented. The point indicates the mean, and the bars indicate a 95% confidence interval. In the usefulness group, "Found useful" includes those who either selected "Useful" or "Somewhat useful", while "Did not find useful" includes those who either selected "Not useful at all" or "Somewhat unuseful".

In further exploratory analyses, we found that income is related to increased awareness (Δ_M = 360€, $p < .001$) and use of SAAs when compared to all nonusers (Δ_M = 407€, $p = .002$). When comparing users with nonusers who were aware of SAAs, we only found a smaller, not statistically significant difference (Δ_M = 126€, $p = .425$). The biggest difference was observed in the usefulness variable: Among those who found SAAs (somewhat) useful, income was on average 964€ higher ($p < .001$) than among those who found them (somewhat) unuseful.

Higher (self-reported) general health was associated with greater knowledge of SAAs (Δ_M = 0.21 on a scale of 1 to 5, p = .004), but not with increased use of them (when compared to all nonusers) (Δ_M = 0.01, p = .511). However, when controlling for awareness of SAAs, users reported lower general health than nonusers (Δ_M = 0.31, p = .013). General health was higher among those who found SAAs (somewhat) useful than among those who did not, but this difference was not statistically significant (Δ_M = 0.51, p = .052).

Self-efficacy was similar for all comparisons, except for usefulness. Those who found SAAs (somewhat) useful had higher self-efficacy levels than those who did not, but the difference was not statistically significant (Δ_M = 0.58 on a scale of 1 to 5, p = .052).

The proportion of respondents undergoing psychotherapy was higher for those who knew of (Δ_M = 6.7 percentage points, p = .007) and used SAAs (in both comparisons, Δ_M = 17.9 percentage points, p < .001 when comparing users with nonusers and Δ_M = 18.8 percentage points, p = .001 when comparing users with nonusers aware of SAAs). The greatest difference was observed in terms of usefulness with a difference of Δ_M = 21.2 percentage points but it was not statistically significant (p = .222).

A visual summary of these exploratory results can be found in Figure 3.

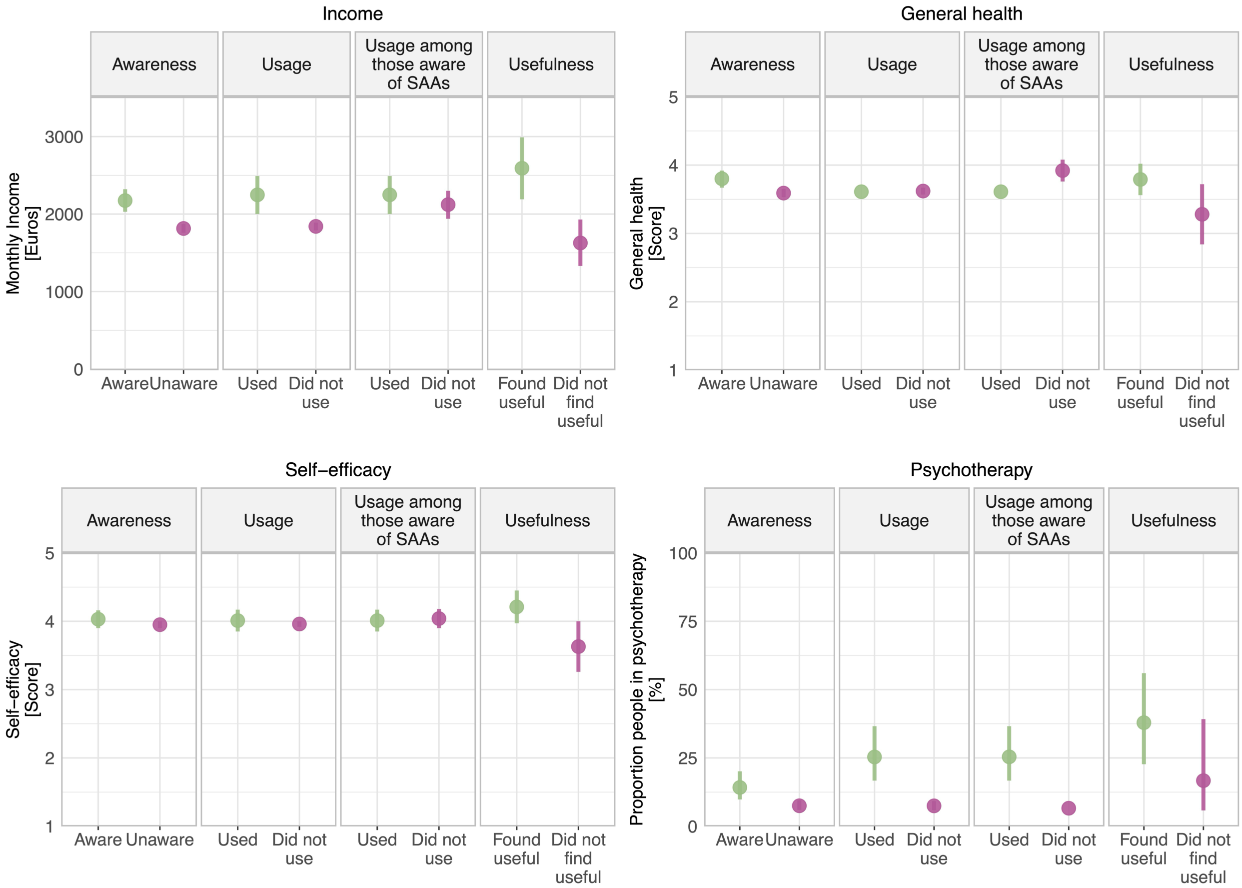

Figure 3: Comparison of income, general health, self-efficacy, and proportion of respondents undergoing psychotherapy among different reference groups; figure based on data from Kopka et al. (60), own representation.

Note: The point indicates the mean, and the bars indicate a 95% confidence interval. In the usefulness group, "Found useful" includes those who either selected "Useful" or "Somewhat useful", while "Did not find useful" includes those who either selected "Not useful at all" or Somewhat unuseful".

3.2 Additional results

There was a weak correlation between knowledge of SAAs and knowledge of other health apps and use of specific eHealth applications (DiGA, ePA). However, using SAAs was not associated with knowledge about specific applications, but with using them (and general health app use) once they knew about them. A moderate correlation exists between usefulness of SAAs and the use of specific other health apps, but a weaker association exists between usefulness and knowledge of those apps; see Table 2.

Table 2: Correlation coefficients of being aware of SAAs, using SAAs and SAA usefulness ratings with awareness of and use of other eHealth applications available in Germany, own creation.

eHealth Application	Aware of SAAs[1]	Has used SAAs[1,a]	Perceived usefulness of SAAs[2,b]
Has used health apps generally	.23****	.25**	.01
Is aware of DiGA	.23****	-.05	.24
Has used DiGA[c]	.14****	.19*	.55
Is aware of ePA	.11***	-.08	.20
Has used ePA[d]	.12***	.22**	.46

Note:
[1] Phi correlation coefficient
[2] Glass rank biserial correlation coefficient
[a] only includes data from individuals who were aware of SAAs
[b] only includes data from individuals who have used SAAs
[c] only includes data from individuals who were aware of DiGA
[d] only includes data from individuals who were aware of the ePA
DiGA = Digitale Gesundheitsanwendungen (health apps covered by health insurance),
ePA = elektronische Patientenakte (electronic health record)
$**** = p < .0001$, $*** = p < .001$, $** = p < .01$, $* = p < .05$

Respondents who were aware of SAAs were more likely to be aware of DiGA (OR = 3.44, p .001) and the ePA (OR = 1.90, $p < .001$) than those who were not aware of SAAs. They also had higher use rates for health apps in general (OR = 3.48, $p < 0.001$), and DiGA (OR = 5.42, $p < 0.001$) and the ePA (OR = 2.92, $p < .001$); see Table 3.

Table 3: Awareness and use of different eHealth applications available in Germany among respondents who are aware of SAAs and among those who are not, own creation.

eHealth Application	Aware of SAAs	Not aware of SAAs
N	177	907
Has used health apps generally, n (%) [95% Confidence Interval %]	128 (72.3%) [65.3 – 78.4%]	389 (42.9%) [39.7 – 46.1%]
Aware of DiGA, n (%) [95% Confidence Interval %]	77 (43.5%) [36.4 – 50.9%]	166 (18.3%) [15.9 – 21.0%]
Has used DiGA, n (%) [95% Confidence Interval %]	12 (6.8%) [3.9 – 11.5%]	12 (1.3%) [0.8 – 2.3%]
Aware of ePA, n (%) [95% Confidence Interval %]	114 (64.4%) [57.1 – 71.1%]	443 (48.8%) [45.6 – 52.1%]
Has used ePA, n (%) [95% Confidence Interval %]	22 (12.4%) [8.4 – 18.1%]	42 (4.6%) [3.4 – 6.2%]

Participants' awareness of DiGA (OR = 0.83, p = .646) and the ePA (OR = 0.68, p = .378) was similar to what was found in the comparison of SAA users to nonusers who were aware of SAAs. However, in terms of use, SAA users more commonly used other health apps generally (OR = 3.55, p = .002), and DiGA (OR = 4.98, p = .025) and the ePA (OR = 3.79, p = .008); see Table 4.

Table 4: Awareness and use of different eHealth applications available in Germany among respondents who use SAAs and among those who do not use them but are aware of them, own creation.

eHealth Application	Has used SAAs	Has not used SAAs (but knows of them)
N	71	106
Has used health apps generally, n (%) [95% Confidence Interval %]	61 (85.9%) [76.0 – 92.2%]	67 (63.2%) [53.7 – 71.8%]
Aware of DiGA, n (%) [95% Confidence Interval %]	29 (40.8%) [30.2 – 52.5%]	48 (45.3%) [36.1 – 54.8%]
Has used DiGA, n (%) [95% Confidence Interval %]	9 (12.7%) [6.8 – 22.4%]	3 (2.8%) [1.0 – 8.0%]
Aware of ePA, n (%) [95% Confidence Interval %]	42 (59.2%) [47.5 – 69.8%]	72 (67.9%) [58.5 – 76.0%]
Has used ePA, n (%) [95% Confidence Interval %]	15 (21.1%) [13.2 – 32.0%]	7 (6.6%) [3.2 – 13.0%]

Other health apps are more commonly used by SAA users for all kinds of functions than by non-SAA users who are aware of them. The three most used functionalities are obtaining information (58/71, 81.7% of users and 68/106, 64.2% of nonusers who are aware); assessing and analyzing health information (49/71, 69.0% of users and 26/106, 24.5% of nonusers who are aware), and buying medical products (49/71, 69.0% of users and 61/106, 57.5% of nonusers who are aware). A major difference can be observed regarding assessment and analysis of health information between users and nonusers who are aware of SAAs (OR = 6.85, $p < .001$). Another major difference can be observed in their use of health apps to track health data (OR = 2.86, $p = .001$). Other functions were more likely to be used by SAA users, but the differences were not statistically significant; see Figure 4.

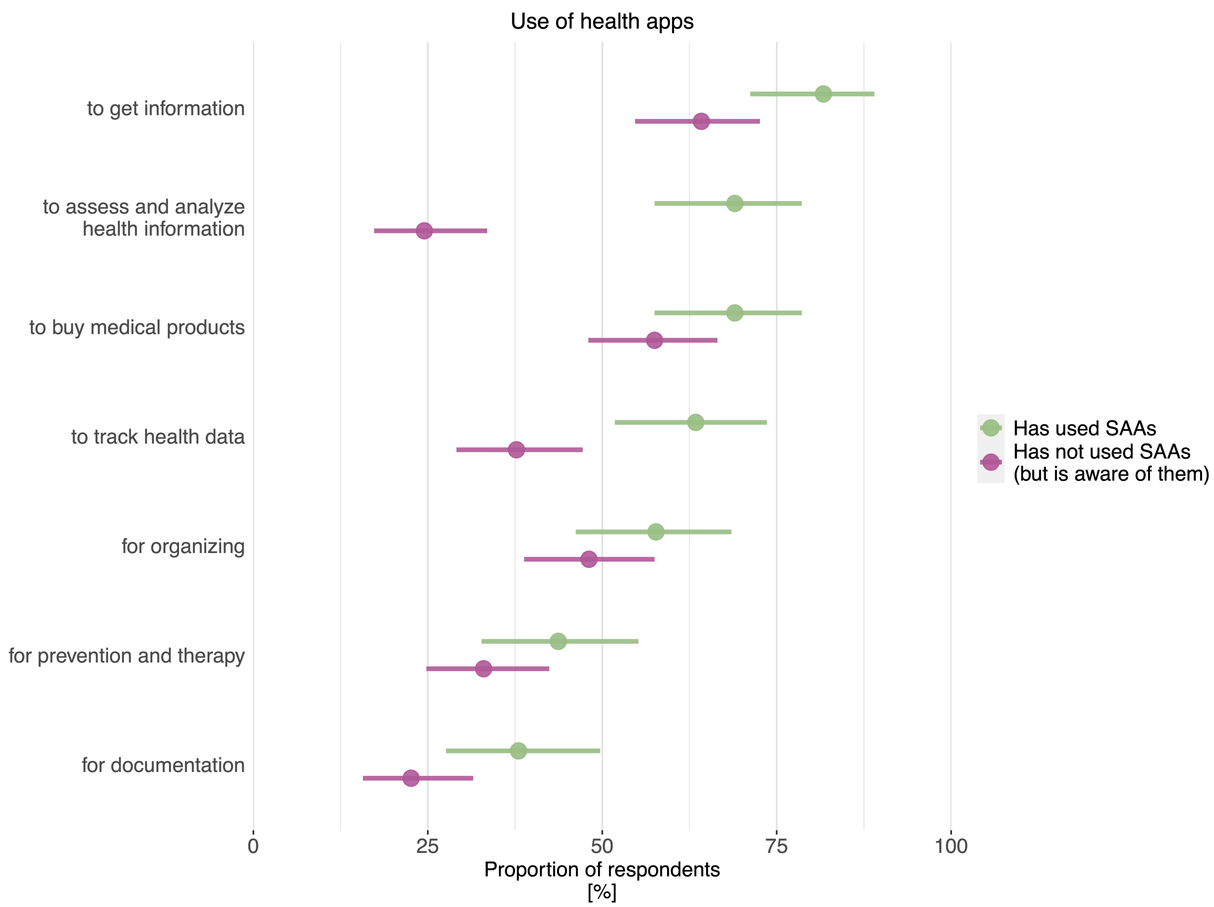

Figure 4: Comparison of SAA users and nonusers who are aware of SAAs with respect to the functionalities for which they use health apps, own representation.

Note: The point indicates the proportion, and the bars indicate a 95% confidence interval.

4. Discussion

In the following section, I will summarize our results and compare them to similar studies on SAAs specifically and eHealth in general. I will then situate the results within previous SAA research before critically discussing the methods we used and pointing out their limitations. Finally, I will propose ideas for future research based on this study and SAA research in general.

4.1 Short summary of results

In this study, I aimed to assess the prevalence of knowing SAAs, using them, and finding them useful. Further, I aimed to explore characteristics associated with awareness, use, and perceived usefulness. Our results show that SAAs are only known to a minority of Germans, and—among them—not even half of them use them. Most characteristics related to the use of SAAs (e.g., gender, age, level of formal education) are associated with awareness and use but not with willingness to use. When analyzing a subset of people who are aware of SAAs (who can decide actively for or against the use), these characteristics differ only slightly. For example, the distribution of gender, age and formal education levels is similar for users and nonusers in this subset. Further, characteristics that are associated with the awareness, use, and willingness to use, do not seem to be associated with usefulness of SAAs. For example, women reported that they knew SAAs more often, but also that they considered them less useful. Contrary, men more often reported considering them useful.
In the context of general eHealth, people aware of SAAs were also aware of other eHealth technologies (such as DiGA or ePA). Using SAAs was also associated with the use of other eHealth technologies, but not with knowledge about them. Lastly, SAA users seem to use health apps more often for information and data-related functions such as obtaining information, analyzing health information, or tracking health data.

4.2 Comparison with similar studies

In our study, we found a lower proportion of SAA users in Germany than previously published, with only 6.5% in our study compared to 13% in a report from 2020 (59). But we did replicate the findings of previous research reporting that SAA users tend more often to be female, younger, and with higher levels of formal education on average

(9,47,49,50,76). However, our study shows that these characteristics seem to be more related to the awareness of SAAs and less to their use. Further support for this conclusion can be found in a report that demonstrates that women and men are about equally willing to use SAAs when they know about them (76). Therefore, our results are in line with previous research and synthesize findings from studies with different sampling approaches (e.g., sampling from symptom checker users, but also from market research surveys). However, it is unclear why these sociodemographic characteristics are associated with greater awareness. According to previous studies, women have on average a higher level of health anxiety than men (77) and do care work for others more frequently (78). As a result, they may be faced with an increased need for health information and thus use SAAs (which can also be used to assess symptoms of others) more frequently. The age effect may be explained by younger generations having more exposure to technology, specifically eHealth, as a result of growing up at a time when technology had become a more everyday part of people's lives (the so-called "age-based digital divide") (79). The higher levels of formal education among those who were aware of SAAs may be explained by their tendency to search for diagnoses online (9), a search which is more than likely to provide information on SAAs. It is unclear, however, why educational levels and searching for diagnoses online are associated. One explanation might be that such a search requires a kind of cognition that is associated with higher levels of education (80,81), but at this point it is not possible to determine the exact (causal) relationship. This lack of causal relationship holds true for all other factors associated with awareness, use, and perceived usefulness of SAAs. A more in-depth comparison with similar studies can be found in Kopka et al. (60).

The comparison of SAA users with users of other German eHealth technologies (namely DiGA and ePA) looks at two different factors: Knowing of eHealth technologies and using them. Our data suggests that SAA knowledge is associated with knowledge of other eHealth technologies but only weakly associated with their use. Similarly, willingness to use SAAs is related to use of other eHealth technologies once they are ware of them, but only weakly related to knowledge about them. It is possible that the observed differences and characteristics are not limited to SAAs but may reflect the characteristics of eHealth users as a whole. Indeed, in similar studies (not focusing exclusively on SAAs), similar characteristics have been found for eHealth users: They were more often female, on average younger, and had higher levels of formal education (16,82–85). Another study also observed these differences in awareness of, but not in willingness to use eHealth technology in general (9).

We did find, however, an association between SAA use and self-reported worse general health, which may not be generalizable to all eHealth users. For example, in a study of Hong Kong residents, those who used eHealth reported better general health than those who did not (84). Worse health that was associated with usage may therefore be a characteristic unique to SAAs and not universal to eHealth in general.

Our data also points to a link between mental health problems and the use and awareness of SAAs. Other studies have specifically examined eHealth interventions for mental health (86), but there is less data on the association between mental health and general eHealth use despite one study showing increased digital technology use among those with severe mental illness (87). Therefore, it is unclear whether this finding is exclusive to—similar to self-reported worse general health—or if it is generalizable to eHealth as a whole. As other studies typically did not collect data on this (47,50,55,56,88), we are unable to confirm whether this result could be replicated for SAAs in other countries and settings.

Among eHealth users, SAA users more often tend to use eHealth specifically for information- and data-related activities. Unfortunately, other studies comparing different use patterns of eHealth technology are lacking—so there is ultimately no evidence for or against this hypothesis supported by the current state of research. To potentially falsify this hypothesis, future studies could examine eHealth users in more detail and differentiate between different applications and use patterns.

4.3 Positioning these results within the current state of research

Most of the characteristics of users reported in previous studies seem to be linked to awareness of rather than a willingness to use SAAs, which means that the promotion of SAAs should not be tailored toward this specific demographic but instead promoted to the general public. Considering that most users follow the advice that they receive from SAAs (46,49,50,52), women—who tend to be more risk-averse than men when deciding on the urgency of symptoms (13,54)—may objectively benefit from SAAs more than men do because SAAs could reduce their perceived urgency level. In our study, however, they were subjectively less likely to consider them useful. Female and male users were not observed to behave differently in following advice, suggesting that SAAs may be objectively useful for both, although further research is needed to confirm this hypothesis. In either case, SAAs appear to be a promising alternative to search engines for obtaining treatment urgency information. Since search engines can potentially provide biased information while making users more certain in their (often incorrect) decisions (18–20), SAAs may prove useful regarding this specific aspect of online health information. Although they may not be the most reliable sources of information either (some SAAs having accuracy issues and only a limited number consistently performing well), their advice is often safe for patients because they lean towards risk-aversion (31,35,40). As more people who use SAAs lower rather than heighten their urgency levels (49), integrating SAAs into its own operations could benefit the healthcare system as well.

In summary, using SAAs for self-diagnosis and care-seeking advice could provide an alternative to search engines for the general public, not just for current users. Although some subgroups may benefit more than others from it (for example, those with higher levels of formal education, higher income, and higher levels of self-efficacy), integration into the healthcare system might nevertheless have overall positive effects.

4.4 Critical discussion of methods and limitations

We used stratified random sampling to match the German population in terms of gender, income, age and federal state. While not relying on non-random sampling techniques such as a convenience sample or a snowball sample (89) is a strength, our sample was drawn from the bilendi/respondi user base and thus might not be fully representative of the German population. For example, participants in our sample had a slightly higher affinity for technology than did another German sample collected offline (3.74 vs. 3.58 on a scale of 1 to 6) (72), which might be a consequence of using the bilendi/respondi user base and of administering the questionnaire online. However, other modes of communication, such as telephone interviews, do not seem to mitigate these biases: According to a comparative study, both methods produce similar results and represent the target population effectively (90). We share this limitation with a series of other studies aiming to sample nationally representative participants using bilendi/respondi (91–95).

A strength of our sample is that we surveyed a broad range of people, rather than limiting our sample to users of specific SAAs as some previous studies have done. For example, Arellano Carmona et al. (47) sampled users of the SAA Buoy, while Meyer et al. (55) selected users of the SAA Isabel and reported several user characteristics similar to ours. Although this approach samples users directly, it is subject to a higher sampling bias when aiming for a sample of general SAA users. For instance, in a 14-day time period (47), users experiencing symptoms more frequently, or caring for others with symptoms, may use SAAs more often and thus be overrepresented in the data collected from these apps. This leads to limited generalizability and low external validity outside of the examined SAAs. Our study instead surveyed a general sample that allowed comparisons of users to nonusers while not relying on specific SAAs and developers. Other approaches in the literature include using a sample of rheumatology outpatient clinic visitors (56) or a random sample of emergency department visitors (23). Although mitigating the problem of a bias toward more tech-savvy individuals (as occurred in our study), the former sample is biased towards people with musculoskeletal symptoms with an unknown diagnosis (as reported in their study) and the latter toward individuals seeking emergency care. Compared to other studies, we consider our sampling approach—although not perfect—to be the most externally valid yet in reporting the characteristics of people who are aware of and use SAAs.

Another limitation concerning our sample is the sample size, which was ultimately determined by resource constraints and the available budget, not based on an a-priori power analysis (with the prevalence rate and error margin or a desired effect size/smallest effect size of interest). However, our study included 1,084 participants, which is similar to the sample size of other studies on the prevalence of eHealth use (62–65). While this sample size seems to be sufficient to estimate, for instance, the rate of SAA users with acceptable confidence interval ranges, some subgroups were small (e.g., users who considered SAAs useful vs. those who did not). Thus, we could not detect smaller effect sizes in these subgroups—in case differences even existed—and were more prone to type II errors. We still found statistically significant differences with bigger effect sizes, however, even in these subgroups with a small sample size. In light of our aim to generate hypotheses and not to confirm them, we consider our sample size sufficient. Future research should replicate and confirm our observations (in confirmatory studies) and explore more differences (in exploratory studies) using a larger (subset) sample size.

Another limitation concerns cross-sectional surveys as a methodology. While they are well-suited for estimating the prevalence of diseases—or in this case the prevalence of SAA awareness and use—they are not suitable for drawing causal inferences (61). For example, previous observational studies found age and gender to be associated with usage (47,55). Our study extends these results by finding that they are not associated with usage itself, but with awareness of SAAs. Awareness thus seems to act as a mediator. Considering as well that we only conducted an observational study (and thus cannot infer causal relationships either), we cannot conclude that awareness is the sole mechanism underlying the relationship between these sociodemographic variables and SAAs. For example, doing more care work (78) could be one of multiple different reasons why women more frequently know about SAAs and use them more often. Another example is income: It was associated with the awareness, use, and perceived usefulness of SAAs. This may not be the true cause of the differences, but rather a reflection of socioeconomic status or different use cases people with higher income approach SAAs with. However, since this study's intent was to assess the current state of SAA awareness and use, explore associated characteristics, and generate hypotheses, we did not seek to establish causal relationships.

One further limitation in survey research is a social desirability bias: Participants might give dishonest answers because they think their honest answers might be socially undesirable (96). Mental health questions may be particularly challenging because of the associated stigma (97). In addition, usefulness, for example, was reported retrospectively and not directly after using an SAA, and thus these answers might be subject to recall bias (98). To avoid high dropout rates, we also had to choose variables carefully. EHealth literacy and more in-depth questions about mental health would have been interesting variables, as well as asking participants about their trust in SAAs as we did in previous studies (23,46). Users were also not asked how frequently they used SAAs. There might be differences between active users who enter symptoms as soon as they experience any and those who only sporadically use SAAs as one piece in their decision-making process.

Closely linked to this study's design is the statistical analysis. Because the variables had different levels of measurement, we had to use a variety of statistical tests for inferential statistics. We carefully selected the most appropriate method (e.g., Fisher's exact test when cell observations were less than 5, or treating Likert-type single-question variables as ordinal and using Mann-Whitney U tests instead of t-tests)—but calculating p-values in exploratory cross-sectional surveys is questionable as it does not equate to the typical use and interpretation of p-values in confirmatory research. That is, we did not have a prespecified hypothesis that we tested. Instead, our explorative p-values could be interpreted as evidence for a new hypothesis that might be worth examining in new studies (99). Although correcting for multiple testing in exploratory research is debatable as well (100), we wanted to take a conservative approach and for that reason conducted robustness analyses with adjusted p-values. Arguably more important than hypothesis testing and reporting p-values is reporting estimates with a quantification of uncertainty. Therefore, we reported the estimates with 95% confidence intervals in Kopka et al. (60).

4.5 Questions for future research

Future research could focus on international comparisons of SAA users and general awareness of SAAs. By focusing on awareness and perceived usefulness, we extended prior findings, and also used a different sampling method: While we surveyed the (online) general public, Arellano Carmona et al. (47), Winn et al. (49) and Meyer et al. (55) conducted surveys of users of specific SAA applications and Knitza et al. (56) and Miller et al. (50) surveyed visitors to care facilities. In spite of the differing approaches and samples from different countries, all came to similar conclusions and found similar characteristics. The different methodologies make exact comparisons difficult. To assess potential differences between countries and healthcare systems, a standardized survey could be conducted in multiple countries. Research on these topics would be of interest not only to researchers, but also to SAA developers who could then tailor their systems to specific user needs in different countries and thereby improve SAA usefulness.

Since we identified influential characteristics that were not reported before (e.g., mental health, general health), it would be worthwhile to replicate these findings in other studies in order to confirm this exploratory result. For example, other characteristics found in this study generally indicate a healthier subpopulation, but when specifically asked about their health, SAA users seemed to be in less-than-optimal health. Additional health-related variables could be explored, such as chronic diseases or attitudes towards healthcare institutions and different stakeholders. In a meta-analysis on vaccine uptake, the authors specifically examined trust in various institutions: In science, the media, the healthcare system, primary healthcare providers, and the government. In the near future, these trust levels might become even more relevant since SAAs are already part of and expected in future to play an even bigger role in the healthcare system (101). An examination of the relationship between trust in SAAs and trust in other institutions could be a promising direction for future research.

Also, additional questions should be included in surveys on SAA awareness and use. Respondents were asked if they had used SAAs before, but not how often. There might be a difference between regular users and those who have used an SAA only a few times before deciding not to continue to use it. A deeper understanding of these differences requires further research. Getting a better understanding of how SAAs are used should also include questions on how often they are used by the respondents for themselves rather than to assist others. Additionally, SAA users could be surveyed as in previous studies but without limiting the sample to users of specific SAAs. Instead, a survey among the general public with being aware of or already using SAAs as inclusion criteria could be conducted. This would allow for more reliable insights, since relying on a particular SAA could potentially lead to a sampling bias. Using this sample (with a larger size than our user-sample subset), new questions like the following could be answered: How useful were the SAAs that they used? Which factors were associated with usefulness? How often do users use SAAs for others? What do they consider important in SAAs? What other functions would be useful?

We hypothesized that SAA users as a subset of eHealth users would share the same (sociodemographic) characteristics as those of general eHealth users. That, however, does not seem to be true for all variables, as eHealth users generally reported better general health (84) and SAA users worse general health. We also found that SAA users more commonly use eHealth technology for analytical and data-related purposes. Thus, while these groups share most characteristics, they seem to differ in some. Future studies could identify these differing characteristics and then describe how SAA users differ from the population of eHealth users and how these differences might influence user-SAA interaction. For example, if the algorithm is optimized for a healthier population (like general eHealth users), less healthy users (more common in SAA data) might get incorrect recommendations made by an SAA designed with a built-in presumption that its users are generally healthy. Similarly, differences in characteristics between SAA users and people seeking health information online could be examined. Since search engines are even more commonly used to assess experienced symptoms or obtain health information—but SAAs provide similar information in a more structured way—these potential differences and barriers to knowing about and using SAAs could be assessed. These barriers could then be mitigated in the future. Further, these insights will be valuable to policy makers once SAAs become integrated into the official care systems to help improve patient flow.

In this study, we asked users about how useful they considered their specific SAA. This procedure is similar to those of other studies (56), but only assesses self-reported usefulness. Even though that opinion is an important aspect of using an SAA, it does not equate to objective usefulness, that is, to making better decisions. There has been extensive research on SAA accuracy (31,35,40,88), but there is little research examining humans and SAAs as a kind of human-machine team that could improve decision-making beyond what individuals can decide on their own. In only one study, triage decisions were assessed before and after the use of an SAA, but the accuracy of decisions did not seem to change (102). Hence, there seems to be a lack of data on how decisions in a human-SAA team are made.

It is also important to identify specific interventions that can improve these "team" decisions. Even if SAAs were perfectly accurate, users might not be able to arrive at completely accurate decisions when using them. Therefore, behavioral science can be used to study self-diagnosis and care-seeking decisions and find ways to improve them. With a diverse toolkit, interventions such as nudges (overcoming cognitive biases to improve decisions by changing the decision environment) or boosts (improving competencies to help people make better decisions) (103) can be tested. A promising place to start might be examining and teaching users heuristics for incorporating SAA advice.

When asking users how useful they considered their encounter with an SAA, we also did not take context into account: SAAs might be more useful when deciding between emergency and non-emergency care than between visiting a healthcare professional or opting for self-care. Our previous study (13) proposed these binary decisions, and participants' specificity and sensitivity varied between the two, suggesting a varying potential for SAAs.

In addition, patients may have different usefulness ratings depending on the use case, for example, obtaining information about diseases or deciding where to seek medical care. Knitza et al. (56) asked participants to rate the usefulness of SAAs when visiting specialized care facilities, while we asked participants in another study to rate them while they were in emergency departments (23). Using them at home or just acquiring new information are other possible use cases that could produce different results. In future studies, perceived usefulness in these varied situations could be compared through a systematic assessment.

A comparison with other assistance in care-seeking choices may help to get a more comprehensive picture of usefulness, both objective and subjective. The use of triage hotlines or Google, for example, is common, but they are not perfect either (11,102). It would be an important landmark study in SAA interaction research to examine the different options laypeople have available to them, their accuracy, and with which they make the best decisions.

Finally, we found that mental health has a large influence on SAA awareness, use, and usefulness, but only two studies have previously considered mental health. The first compared adverse effects (such as anxiety) generated by use of SAAs and Google (104), while the second investigated the diagnostic accuracy of SAAs for mental health conditions (105). Because we are the first to report an association between mental health and SAA use, a whole subfield remains unexplored. In particular, anxiety disorders might be interesting, since typical reservations about SAAs are the fear of incorrect recommendations and a rise in anxiety levels (105). Identifying how SAA use impacts anxiety and "cyberchondria" and identifying subgroups at higher risk would be a critical next step in research on SAAs. There are, however, other conditions that need to be considered as well. People with depression, for example, were five times more willing to use SAAs, but the reason for that is unclear. After confirming our findings in other studies, qualitative studies with a clinical sample could shed light on these differences and find explanations that can be tested quantitatively in further studies.

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Statutory Declaration

“I, Marvin Kopka, by personally signing this document in lieu of an oath, hereby affirm that I prepared the submitted dissertation on the topic Exploring the adoption of symptom-assessment applications in Germany: An investigation of awareness, use, and usefulness / Die Verbreitung von Symptom Checker Anwendungen in Deutschland: Eine Untersuchung zur Bekanntheit, Nutzung und Nützlichkeit, independently and without the support of third parties, and that I used no other sources and aids than those stated.
All parts which are based on the publications or presentations of other authors, either in letter or in spirit, are specified as such in accordance with the citing guidelines. The sections on methodology (in particular regarding practical work, laboratory regulations, statistical processing) and results (in particular regarding figures, charts and tables) are exclusively my responsibility.

Furthermore, I declare that I have correctly marked all of the data, the analyses, and the conclusions generated from data obtained in collaboration with other persons, and that I have correctly marked my own contribution and the contributions of other persons (cf. declaration of contribution). I have correctly marked all texts or parts of texts that were generated in collaboration with other persons.

My contributions to any publications to this dissertation correspond to those stated in the below joint declaration made together with the supervisor. All publications created within the scope of the dissertation comply with the guidelines of the ICMJE (International Committee of Medical Journal Editors; http://www.icmje.org) on authorship. In addition, I declare that I shall comply with the regulations of Charité – Universitätsmedizin Berlin on ensuring good scientific practice.

I declare that I have not yet submitted this dissertation in identical or similar form to another Faculty.

The significance of this statutory declaration and the consequences of a false statutory declaration under criminal law (Sections 156, 161 of the German Criminal Code) are known to me.”

Date Signature

Declaration of your own contribution to the publications

Marvin Kopka contributed the following to the below listed publication:

Publication 1: Kopka, M, Scatturin L, Napierala H, Fürstenau D, Feufel MA, Balzer F, et al. Characteristics of Users and Nonusers of Symptom Checkers in Germany: Cross-Sectional Survey Study. J Med Internet Res. 2023 Jun 20;25:e46231. https://doi.org/10.2196/46231

Contribution (please set out in detail):

- I developed the research question, conceived the study and created the questionnaire in collaboration with Malte Schmieding and Hendrik Napierala
- I conducted the literature research with Lennart Scatturin
- I conducted the data cleaning myself
- I designed, conducted and interpreted the statistical analyses myself
- I did the data visualization myself
- All tables were created by myself
- All figures were created by myself
- The first draft of the manuscript was written by myself
- All authors worked on manuscript development
- I handled the manuscript submission myself
- I presented parts of the study at the 24. Jahrestagung des Deutschen Netzwerks Evidenzbasierte Medizin e.V. and the 4. Charité-Versorgungsforschungskongress

Signature, date and stamp of first supervising university professor / lecturer

Signature of doctoral candidate

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JOURNAL OF MEDICAL INTERNET RESEARCH Kopka et al

Original Paper

Characteristics of Users and Nonusers of Symptom Checkers in Germany: Cross-Sectional Survey Study

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Abstract

Background: Previous studies have revealed that users of symptom checkers (SCs, apps that support self-diagnosis and self-triage) are predominantly female, are younger than average, and have higher levels of formal education. Little data are available for Germany, and no study has so far compared usage patterns with people's awareness of SCs and the perception of usefulness.

Objective: We explored the sociodemographic and individual characteristics that are associated with the awareness, usage, and perceived usefulness of SCs in the German population.

Methods: We conducted a cross-sectional online survey among 1084 German residents in July 2022 regarding personal characteristics and people's awareness and usage of SCs. Using random sampling from a commercial panel, we collected participant responses stratified by gender, state of residence, income, and age to reflect the German population. We analyzed the collected data exploratively.

Results: Of all respondents, 16.3% (177/1084) were aware of SCs and 6.5% (71/1084) had used them before. Those aware of SCs were younger (mean 38.8, SD 14.6 years, vs mean 48.3, SD 15.7 years), were more often female (107/177, 60.5%, vs 453/907, 49.9%), and had higher formal education levels (eg, 72/177, 40.7%, vs 238/907, 26.2%, with a university/college degree) than those unaware. The same observation applied to users compared to nonusers. It disappeared, however, when comparing users to nonusers who were aware of SCs. Among users, 40.8% (29/71) considered these tools useful. Those considering them useful reported higher self-efficacy (mean 4.21, SD 0.66, vs mean 3.63, SD 0.81, on a scale of 1-5) and a higher net household income (mean EUR 2591.63, SD EUR 1103.96 [mean US $2798.96, SD US $1192.28], vs mean EUR 1626.60, SD EUR 649.05 [mean US $1756.73, SD US $700.97]) than those who considered them not useful. More women considered SCs unhelpful (13/44, 29.5%) compared to men (4/26, 15.4%).

Conclusions: Concurring with studies from other countries, our findings show associations between sociodemographic characteristics and SC usage in a German sample: users were on average younger, of higher socioeconomic status, and more commonly female compared to nonusers. However, usage cannot be explained by sociodemographic differences alone. It rather seems that sociodemographics explain who is or is not aware of the technology, but those who are aware of SCs are equally likely to use them, independently of sociodemographic differences. Although in some groups (eg, people with anxiety disorder), more participants reported to know and use SCs, they tended to perceive them as less useful. In other groups (eg, male participants), fewer respondents were aware of SCs, but those who used them perceived them to be more useful. Thus, SCs should be designed

to fit specific user needs, and strategies should be developed to help reach individuals who could benefit but are not aware of SCs yet.

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KEYWORDS

symptom checker; cross-sectional study; user characteristic; digital public health; health information seeking; decision support; eHealth; mHealth; Germany; mobile health; health app; information seeking; technology use; usage; demographic; perception; awareness; adoption

Introduction

Background

Worldwide, health experts are expecting an increasing shortage of medical personnel within the next few years [1-3]. Especially in rural areas, access to medical care is expected to decline [4]. Thus, it will become increasingly important for patients to inform themselves about their medical condition and to take the right steps based on this information. Symptom checkers (SCs) support this process of self-management [1]: these systems are defined as patient-facing decision support systems—typically using deep learning (eg, recurrent neural networks), Bayesian networks, or rule-based algorithms [5-8]—that enable laypersons to get preliminary diagnoses and recommendations for the level of care to seek based on their symptoms [8]. Like other sources of online health information [9], SCs provide health information in a convenient and scalable way.

One possible risk that emerges from the increasingly widespread usage of SCs is that they amplify existing health inequities. It is already known that racial/ethnic minorities, rural residents, and persons with a low income experience worse health care than others [10,11]. Ahmed et al [12] found that sociodemographic determinants, such as age, gender, education, and income, have an influence on the usage of electronic devices to access health information. Conversely, some authors suggest that mobile decision support systems could alleviate access problems as they provide accessible and easy-to-understand health information [13,14]. To prevent health inequities and to maximize the potential benefits of SCs, it is crucial to understand the factors that contribute to people using and not using them.

SCs commonly offer 2 features to their users: (1) Users can improve their self-diagnosis by obtaining a rank-ordered list of the most likely diagnoses, and (2) SCs can be used to assist with triage decisions. This means that they advise patients on whether it is necessary to seek care at all and, if so, how urgently (eg, instantly or within some days) they should visit which health care facility (eg, emergency department or general practitioner) [15]. Especially, the accuracy and safety of this triage function is an ongoing topic of concern for both patients and health care professionals. Their performance seems to be mediocre on average, with high variability between them [16,17].

Related Work

Prior related studies have mainly focused on the effects of sociodemographic factors on the intention to use, trust in, or adherence to decision support systems in general. Age, gender, the level of education, and several individual factors have been already found to influence the interaction with and usage of SCs specifically. These findings will be briefly summarized next.

Users of SCs tend to be younger (with a mean age of about 40 years), and the willingness to use SCs seems to decline with increasing *age* [18-22]. However, younger users seem to find SCs more useful, but older users have been found to be more likely to recommend them [19,23].

Users also seem more commonly to be female (estimates range from 62% to 85%), although gender has also been reported to not impact the willingness to use such tools [19,20,22].

Lastly, users of SCs tend to have higher levels of formal education, which is associated with an increased likelihood of searching for diagnoses online [8,20,24-27].

In addition to sociodemographic factors, previous studies have found that people with higher *eHealth literacy* are more inclined to use mobile health apps in general and that a lack of computer literacy seems to be one of the greatest barriers to using SCs [22,28,29].

Another relevant interindividual trait is trust, as incorrect diagnoses and increased anxiety are the main concerns when using SCs [22,30]. Thus, (the propensity to) *trust* is found to impact the interaction with SCs as well [31].

Most quantitative findings on SC users stem to date from studies investigating samples using a single SC only. Although users generally perceive SCs as useful [32,33], a lack of awareness of these tools has been discussed as a potential barrier to broader adoption [34].

Objective

The aim of this work is to refine our understanding of how sociodemographic and interindividual characteristics influence the awareness, usage, and perceived usefulness of SC apps. In contrast to most of the previous research that is based on UK, US, or Canadian users of specific SCs (which might not be representative for SC users in general), we investigated a representative sample of German-speaking internet users. Building upon the existing literature, our paper focuses on factors previously shown to be relevant in other countries. Unlike most previous studies on SC users, we sampled not only users but also nonusers of SCs. This broader sampling approach allowed us to address more questions, for example, investigating the potential reasons for unequal usage of SCs across sociodemographic factors. Not being limited to the user group of a specific SC, our approach also yielded more generalizable findings concerning factors influencing usage in the population.

Methods

Study Design, Participants, and Sampling

We conducted a cross-sectional online survey among German residents between July 15 and 26, 2022. Our aim was to sample 1000 participants. No prior sample size calculation was conducted, as the sample size was ultimately determined by the available budget. Considering that some participants were expected to respond incorrectly to control questions, we planned to oversample by 10% (resulting in about 1100 participants). Stratified random sampling was used to sample participants using the ISO 26362–certified sampling provider Bilendi/respondi [35]. We stratified the sample by gender, federal state, income, and age to reflect the German population [36]. Bilendi/respondi was selected because it is a commercial provider that is certified, offers panel surveys with stratified random samples, and has been used by other authors for surveying nationally representative samples in biomedical research [37-39].

The study included participants who were at least 18 years old, and excluded underage participants and those who refused to consent. Moreover, we excluded data from analysis if a participant answered one of the embedded control questions incorrectly. Upon completion, participants received a payment of EUR 1.00 (US $1.08) for their participation.

Ethical Considerations

This study was approved by the Ethics Committee of the Charité – Universitätsmedizin Berlin (EA4/018/22). Prior to enrollment, participants provided informed consent and volunteered to take part in the survey. The study was conducted and reported according to the Checklist for Reporting Results of Internet E-Surveys (CHERRIES) guideline [40].

Survey and Instruments

We developed a survey in German and administered it as an online questionnaire using the Unipark EFS Survey [41]. The authors and a sufficiently large convenience sample (N=9) [42] from the authors' personal and professional network conducted pretests of the survey to ensure comprehensibility of the questions and usability of the online survey and identify any technical issues. We rearranged the survey sections and simplified the language of the questions following the pretest. All collected data were stored in EFS Survey accessible only to the authors. Participants filled out the survey remotely upon an invitation from the sampling provider, and they were prevented from participating more than once by assessing their pseudonymized ID assigned by Bilendi/respondi. The assigned ID was not shared with the authors.

Overall, the survey had 4 sections: (1) sociodemographic and interindividual characteristics, (2) questions about previously received diagnoses and medical care, (3) the usage of technology and health apps in general, and (4) the usage of SC apps in particular.

The questions about demographics and characteristics included age, gender, the level of formal education, the federal state (Bundesland) participants reside in, the municipality size, the disposable income (assessed using the Organisation for Economic Co-operation and Development [OECD]–modified scale [43]), their migration background, and their self-efficacy (measured using the Allgemeine Selbstwirksamkeit Kurzskala, ASKU, [44]).

In the second section (diagnoses and medical care), we asked participants to fill out the Minimum European Health Module (MEHM) [45] to rate their self-perceived health, including activity limitations and chronic morbidity. We also presented them with a selection of different diseases (for which officially approved health apps are available in Germany), and they could choose all diagnoses that applied to them, including depression, panic or anxiety disorder, and chronic pain. Health care usage was assessed by asking for the insurance type (statutory, private, other, or none), whether they have a permanent general practitioner (yes/no), how often they visited a general practitioner within the last 12 months (open numerical text field), whether they are undergoing psychotherapy, and whether they have been hospitalized as an inpatient in the past 12 months (yes/no). We included psychotherapy in our definition of health care usage as the German statutory health insurances cover mental health services and many digital health apps, including SCs, are sought for psychiatric or psychosomatic issues.

In the third section, we asked participants how often they use the internet (several times a day, once a day, several times a week, several times a month, or less than once a month) and we assessed their affinity for technology interaction (using the Affinity for Technology Interaction [ATI] scale [46]). We also assessed their health app usage by asking whether they generally use health apps (yes/no).

In the last section, we gave participants a description of SCs and asked them about SCs using 3 steps: First, we asked whether they know about SCs (yes/no). If they affirmed, they were asked whether they had used them before (yes/no). If they did, we asked them to rate their usefulness on a 5-point Likert scale with the levels 1="not useful at all," 2="rather not useful," 3="sometimes useful, sometimes not," 4="rather useful," and 5="very useful."

We embedded 2 control questions in the questionnaire asking participants to select a particular answer option to a mock question (eg, "Please select 'does not apply'").

Data Analysis

The data were analyzed exploratively—all values (including *P* values along with other measures of statistical inference) should therefore be interpreted in a hypothesis-generating manner. We included robustness checks (see Multimedia Appendix 1) adjusting *P* values for multiple testing using the Benjamini-Hochberg procedure to verify that the results remained valid after correction. Our significance level was set to .05. For income, we controlled for unreasonable data by excluding outliers (defined as the top 2.5% and the bottom 2.5% income).

First, we compared those aware of SCs and those unaware of them. Second, we compared SC users with nonusers, (1) in all participants and (2) in a subset of those being aware of SCs, to assess factors that may contribute to the willingness to use.

Lastly, to assess factors influencing the perceived usefulness of SCs, we included only data from participants who had used SCs before. We divided usefulness into “not useful” (indicated by selecting “not useful at all” or “rather not useful”), a middle category (“sometimes useful, sometimes not”), and “useful” (indicated by selecting “rather useful” or “very useful”).

We conducted comparative analyses of these subsets by comparing all characteristics using summary statistics (mean and SD for metric variables, absolute numbers, percentages, and 95% CIs for binary, multinomial, and ordinal variables). For inferential analyses, we used Welch *t* tests (for metric variables with groups of different sample sizes); chi-square tests (for binary and multinomial variables), or Fisher exact tests when any cell contained less than 5 observations; and Mann-Whitney U tests (for ordinal variables). To quantify effect sizes, we used Cohen d for *t* tests, the phi coefficient (ϕ) for 2×2 chi-square tests/Fisher exact tests, Cramer V for more than 2×2 chi-square tests/Fisher exact tests, and the Glass rank biserial correlation coefficient rg for Mann-Whitney U tests. Further, we visualized selected characteristics in raincloud plots [47].

In Multimedia Appendix 1, we provide the following additional analysis: To explore perceived usefulness in more detail, we correlated usefulness with other binary (point-biserial correlation) and continuous variables (Pearson correlation) and visualized it in a heatmap using 1 column of a correlation matrix.

We used R version 4.1.2 [48] and the *tidyverse* packages [49] to manipulate and analyze the collected data. We also used the packages *rstatix* [50] to compute summary statistics and correlation matrices; *DAAG* [51] to assess the variance inflation factors; *ggdist* [52] and *gghalves* [53], in addition to *ggplot2* [54], for data visualization; and *DescTools* [55] to compute CIs. For effect size computation, we used *rstatix* (Cohen d), *rcompanion* (Glass rank biserial correlation coefficient rg) [56], *DescTools* (Cramer V), and the *psych* package (ϕ) [57].

To make the Results section more concise, mostly statistically significant results are reported in tables summarizing group comparisons of participant characteristics. Detailed tables outlining all findings and inferential statistics are provided in Multimedia Appendix 1.

Results

Participants

A total of 1555 people accessed the survey, of which 400 (25.7%) did not complete it. Moreover, 4 (0.3%) participants were screened out: 2 (50.0%) for indicating to be younger than 18 years and 2 (50.0%) for not providing informed consent. We excluded the data of 67 (4.3%) participants due to incorrect answers to at least 1 of 2 control questions. As a result, we included the data of 1084 (69.7%) participants in our study. About 1 in 6 participants (177/1084, 16.3%) indicated having previously heard about SCs. Of these, 40.1% (71/177)—equating to 6.5% (71/1084) of the total sample—reported having used an SC at least once before. Participants’ characteristics (with all collected variables) are shown in Table 1.

Table 1. Characteristics of respondents (N=1084).

Characteristics	Respondents
Age (years), mean (SD)	46.7 (15.9)
Gender, n (%)	
Male	521 (48.0)
Female	560 (51.7)
Diverse	3 (0.3)
Education, n (%)	
No school diploma	5 (0.5)
Primary school/lower secondary school	61 (5.6)
Secondary school leaving certificate	225 (20.8)
A level/high school diploma	166 (15.3)
Completed vocational training	317 (29.2)
University or college degree	310 (28.6)
Monthly net household income (EUR/US $[a]), mean (SD)	1868.82 (894.45)/2018.33 (966.01)
Municipality size, n (%)	
<5000	178 (16.4)
5000-10,000	129 (11.9)
10,000-20,000	146 (13.5)
20,000-50,000	168 (15.5)
50,000-100,000	101 (9.3)
100,000-500,000	196 (18.1)
>500,000	166 (15.3)
Migration background, n (%)	123 (11.3)
Native German speaker, n (%)	1044 (96.3)
Self-efficacy, mean (SD)[b]	3.96 (0.72)
General health, n (%)	
Very bad	15 (1.4)
Bad	97 (8.9)
Fair	301 (27.8)
Good	540 (49.8)
Very good	131 (12.1)
Restrictions for health reasons, n (%)	
Not limited at all	459 (42.3)
Limited but not severely	475 (43.8)
Severely limited	150 (13.8)
Diagnosis, n (%)	
Chronic disease	544 (50.2)
Depression	166 (15.3)
Panic or anxiety disorder	110 (10.1)
Chronic pain	141 (13.0
Type of health insurance, n (%)	
Without health insurance	4 (0.4)

Characteristics	Respondents
Statutory health insurance	958 (88.4)
Private health insurance	114 (10.5)
Other	7 (0.6)
Permanent general practitioner, n (%)	984 (90.8)
Number of physician visits in the past year, mean (SD)	3.87 (6.15)
In psychotherapy, n (%)	93 (8.7)
At least 1 inpatient hospital stay in the past year, n (%)	171 (15.8)
Frequency of internet use, n (%)	
Multiple times a day	996 (91.9)
Once a day	65 (6.0)
Multiple times a week	19 (1.8)
Multiple times a month	2 (0.2)
Less than once a month	2 (0.2)
Affinity for technology, mean (SD)[c]	3.74 (1.0)
General health app usage, n (%)	517 (48.5)

[a]EUR 1.00=US $1.08.
[b]On a scale of 1-5.
[c]On a scale of 1-6.

Comparison Between Participants Aware and Unaware of SC Apps

Participants aware of SCs were commonly younger (mean 38.8, SD 14.6 years, vs mean 48.3, SD 15.7 years; *P*<.001), were more commonly female (107/177, 60.5%, vs 453/907, 49.9%; *P*=.015), had higher formal education levels (eg, 72/177, 40.7%, vs 238/907, 26.2%, with a university r college degree; *P*<.001), and on average reported a higher net household income (mean EUR 2173.96, EUR SD 992.83 [mean US $2347.88, SD US $1072.26], vs mean EUR 1813.79, SD EUR 865.37 [mean US $1958.89, SD US $934.60]; *P*<.001) than the remaining study participants. About three-quarters of the participants being aware of SCs (128/177, 74.0%) reported prior experience of using health apps in general in contrast to the remaining participants, of which less than half reported this (389/907, 43.5%; *P*<.001). They also showed higher scores on the ATI scale (mean 4.17, SD 0.93, vs mean 3.66, SD 0.99; *P*<.001). We found only little differences between these groups regarding self-reported general health and migration background. A summary of all characteristics and interindividual differences between those who knew SCs and those who did not is provided in Table 2 and Table S1 in Multimedia Appendix 1.

Table 2. Characteristics of and interindividual differences between respondents aware and not aware of SCs[a].

Characteristics	Aware of SCs	Not aware of SCs
Participants, n (%); 95% CI	177 (16.3); 14.2%-18.7%	907 (83.7); 81.3%-85.8%
Age (years), mean (SD)	38.8 (14.6)	48.3 (15.7)
Gender, n (%); 95% CI		
Male	69 (39.0); 32.2%-46.8%	452 (49.8); 46.5%-53.3%
Female	107 (60.5); 53.7%-68.3%	453 (49.9); 46.6%-53.4%
Diverse	1 (0.6); 0.0%-8.4%	2 (0.2); 0.0%-3.7%
Education, n (%); 95% CI		
No school diploma	0 (0.0); 0.0%-7.8%	5 (0.6); 0.0%-4.0%
Primary school/lower secondary school	7 (4.0); 0.0%-11.8%	54 (6.0); 2.5%-9.4%
Secondary school leaving certificate	27 (15.3); 7.9%-23.1%	198 (21.8); 18.4%-25.3%
A level/high school diploma	35 (19.8); 12.4%-27.6%	131 (14.4); 11.0%-17.9%
Completed vocational training	36 (20.3); 13.0%-28.2%	281 (31.0); 27.6%-34.4%
University or college degree	72 (40.7); 33.3%-48.5%	238 (26.2); 22.8%-29.7%
Monthly net household income (EUR/US $[b]), mean (SD)	2173.96 (992.83)/2347.88 (1072.26)	1813.79 (865.37)/1958.89 (934.60)
General health, n (%) ; 95% CI		
Very bad	2 (1.1); 0.0%-8.9%	13 (1.4); 0.0%-4.9%
Bad	10 (5.6); 0.0%-13.4%	87 (9.6); 6.3%-13.1%
Fair	43 (24.3); 16.9%-32.1%	258 (28.4); 25.1%-31.9%
Good	89 (50.3); 42.9%-58.1%	451 (49.7); 46.4%-53.2%
Very good	33 (18.6); 11.3%-26.4%	98 (10.8); 7.5%-14.3%
Panic or anxiety disorder, n (%); 95% CI	27 (15.3); 10.7%-21.3%	83 (9.2); 7.4%-11.2%
Type of health insurance, n (%); 95% CI		
Without health insurance	0 (0); 0.0%-5.4%	4 (0.4); 0.0%-2.4%
Statutory health insurance	147 (83.1); 78.0%-88.5%	811 (89.5); 87.5%-91.4%
Private health insurance	29 (16.4); 11.3%-21.8%	85 (9.4); 7.5%-11.3%
Other	1 (0.5); 0.0%-6.0%	6 (0.7); 0.0%-2.6%
Permanent general practitioner, n (%); 95% CI	153 (86.4); 80.6%-90.7%	831 (91.6); 89.6%-93.3%
In psychotherapy, n (%); 95% CI	25 (14.2); 9.8%-20.1%	68 (7.5); 6.0%-9.5%
Affinity for technology, mean (SD)[c]	4.17 (0.93)	3.66 (0.99)
General health app usage, n (%); 95% CI	128 (74.0); 67.0%-80.0%	389 (43.5); 40.3%-46.8%

[a]SC: symptom checker.
[b]EUR 1.00=US $1.08.
[c]On a scale of 1-6.

Comparison Between Participants Using and Not Using SC Apps

First, we present results comparing users and all other participants, allowing us to compare the characteristics of users and the general public. To assess the inclination to use SCs, we contrasted the characteristics of users and nonusers in the subset of participants who were aware of these tools.

Comparison Between SC Users and All Remaining Participants

Compared to all nonusers (mean 47.3, SD 15.8), SC users were younger (mean 37.6, SD 14.3 years; $P<.001$; see Figure 1 and Table 3) and more likely to be female (44/71, 62.0%, vs 516/1013, 50.9%; $P=.030$). SC users also had a higher level of formal education: 84.5% (60/71) had a high school diploma, had completed vocational training, or had a university degree compared to 72.4% (733/1013) of nonusers ($P=.035$). SC users also reported a higher net household income on average (mean EUR 2248.18, SD EUR 1052.60 [mean US $2428.03 SD US

$1136.81], vs mean EUR 1841.16, SD EUR 876.04 [mean US $1988.45, SD US $946.12]; *P*=.002). They more commonly indicated restrictions due to health reasons (54/71, 76.1%, vs 571/1013, 56.3%; *P*=.002) and to suffer from a mental illness (29/71, 40.8%, vs 197/1013, 19.4%; *P*<.001; see Table 3). SC users had a higher affinity for technology (mean 4.13, SD 0.95) compared to nonusers (mean 3.72, SD 1.00; *P*<.001) and more commonly used other health apps (61/71, 87.1%, vs 456/1013, 45.7%; *P*<.001). Table 3 and Table S2 in Multimedia Appendix 1 provide additional characteristics and interindividual differences.

Figure 1. Age distribution of SC users and nonusers. SC: symptom checker.

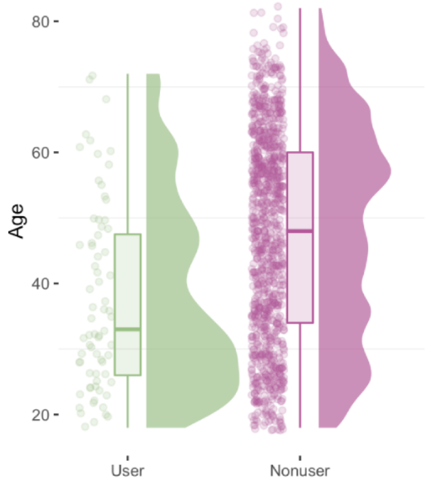

Table 3. Characteristics of and interindividual differences between SC[a] users and nonusers.

Characteristics	Users	Nonusers
Participants, n (%); 95% CI	71 (6.5); 5.2%-8.2%	1013 (93.5); 91.8%-94.9%
Age (years), mean (SD)	37.6 (14.3)	47.3 (15.8)
Gender, n (%); 95% CI		
Male	26 (36.6); 26.8%-49.0%	495 (48.9); 45.7%-52.1%
Female	44 (62.0); 52.1%-74.4%	516 (50.9); 47.8%-54.2%
Diverse	1 (1.4); 0.0%-13.8%	2 (0.2); 0.0%-3.5%
Education, n (%); 95% CI		
No school diploma	0 (0); 0.0%-12.2%	5 (0.5); 0.0%-3.8%
Primary school/lower secondary school	4 (5.6); 0.0%-17.8%	57 (5.6); 2.5%-9.0%
Secondary school leaving certificate	7 (9.9); 0.0%-22.0%	218 (21.5); 18.4%-24.9%
A level/high school diploma	14 (19.7); 8.5%-31.9%	152 (15.0); 11.8%-18.3%
Completed vocational training	16 (22.5); 11.3%-34.7%	301 (29.7); 26.6%-33.1%
University or college degree	30 (42.3); 31.0%-54.4%	280 (27.6); 24.5%-31.0%
Monthly net household income (EUR/US $[b]), mean (SD)	2248.18 (1052.60)/2428.03 (1136.81)	1841.16 (876.04)/1988.45 (946.12)
Restrictions for health reasons, n (%); 95% CI		
Not limited at all	17 (23.9); 12.7%-35.7%	442 (43.6); 40.4%-47.0%
Limited but not severely	40 (56.3); 45.1%-68.1%	435 (42.9); 39.7%-46.3%
Severely limited	14 (19.7); 8.5%-31.5 %	136 (13.4); 10.2%-16.8%
Diagnosis, n (%); 95% CI		
Depression	22 (31.0); 21.4%-42.5%	144 (14.2); 12.2%-16.5%
Panic or anxiety disorder	16 (22.5); 14.4%-33.5%	94 (9.3); 7.6%-11.2%
Currently undergoing psychotherapy, n (%); 95% CI	18 (25.4); 16.7%-36.6%	75 (7.5); 5.9%-9.2%
At least 1 inpatient hospital stay in the past year, n (%); 95% CI	21 (29.6); 20.2%-41.0%	150 (14.8); 12.8%-17.1%
Affinity for technology, mean (SD)[c]	4.13 (0.95)	3.72 (1.00)
General health app usage, n (%); 95% CI	61 (85.9); 76.0%-92.2%	456 (45.7); 42.0%-48.1%

[a]SC: symptom checker.
[b]EUR 1.00=US $1.08.
[c]On a scale of 1-6.

Comparison Between SC Users and Nonusers Aware of SCs

When comparing SC users (n=71, 6.5%) with the remaining participants who were aware of SCs but without prior experience using them (n=106, 9.8%), some differences remained, while others disappeared: age (mean 37.6, SD 14.3 years, vs mean 39.6, SD 14.8 years; *P*=.380), gender (*P*=.464), and net household income distribution were similar between these groups (mean EUR 2248.18, SD EUR 1052.60 [mean US $2428.03, SD US $1136.81], vs mean EUR 2122.00, SD EUR 951.70 [mean US $2291.76, SD US $1027.84]; *P*=.425). Affinity for technology was about equal (mean 4.13, SD 0.95, vs mean 4.19, SD 0.91; *P*=.627), too, and similar to the comparison of users and nonusers, self-efficacy was not associated with the awareness or usage of SC apps.

New differences between these groups appeared regarding health-related factors: Users reported worse general health. Of the 71 users, 6 (8.4%) reported very bad or bad health compared to 6/106 (5.6%) nonusers, 7 (9.9%) reported very good health compared to 26/106 (24.5%) nonusers (*P*=.009), and 54 (76.1%) reported more health-related restrictions compared to 53/106 (51.9%) nonusers (*P*=.001); in addition, users reported more frequent physician visits (mean 4.51, SD 3.69) compared to nonusers (mean 3.08, SD 3.81; *P*=.014). We found the rate of SC usage to be higher among those self-reporting depression (22/71, 31.0%, vs 9/106, 8.5%; *P*<.001), self-reporting panic or anxiety disorder (16/71, 22.5%, vs 11/106, 10.4%; *P*=.046), and undergoing psychotherapy (18/71, 25.4%, vs 7/106, 6.6%; *P*=.001). Tabular and graphical summaries of sociodemographic characteristics and interindividual differences between users and nonusers aware of SCs are provided in Table 4, Table S3 in Multimedia Appendix 1, and Figure S2 in Multimedia Appendix 1.

Table 4. Characteristics of and interindividual differences between SC[a] users and nonusers among respondents aware of SCs.

Characteristics	Using SCs	Aware of but not using SCs
Participants, n (%); 95% CI	71 (40.1); 32.8%-47.7%	106 (59.9); 52.3%-67.2%
General health, n (%); 95% CI		
Very bad	1 (1.4); 0.0%-13.5%	1 (0.9); 0.0%-11.0%
Bad	5 (7.0); 0.0%-19.2%	5 (4.7); 0.0%-14.7%
Fair	22 (31.0); 19.7%-43.1%	21 (19.8); 10.4%-29.8%
Good	36 (50.7); 39.4%-62.8%	53 (50.0); 40.6%-60.0%
Very good	7 (9.9); 0.0%-22.0%	26 (24.5); 15.1%-34.5%
Restrictions for health reasons, n (%); 95% CI		
Not limited at all	17 (23.9); 12.7 –35.7%	53 (50.0); 40.6%-60.2%
Limited but not severely	40 (56.3); 45.1%-68.1%	40 (39.6); 28.3%-47.9%
Severely limited	14 (19.7); 8.5%-31.5 %	13 (12.3); 2.8%-22.5%
Diagnosis, n (%); 95% CI		
Chronic disease	41 (57.7); 46.2%-68.5%	42 (39.6); 30.8%-49.1%
Depression	22 (31.0); 21.4%-42.5%	9 (8.5); 4.5%-15.4%
Panic or anxiety disorder	16 (22.5); 14.4%-33.5%	11 (10.4); 5.9%-17.6%
Permanent general practitioner, n (%); 95% CI	67 (94.4); 86.4%-97.8%	86 (81.1); 72.6%-87.4%
Number of physician visits in the past year, mean (SD)	4.51 (3.69)	3.08 (3.81)
Currently undergoing psychotherapy, n (%); 95% CI	18 (25.4); 16.7%-36.6%	7 (6.6); 3.2%-13.0%
At least 1 inpatient hospital stay in the past year, n (%); 95% CI	21 (29.6); 20.2%-41.0%	15 (14.2); 8.8%-22.0%
General health app usage, n (%); 95% CI	61 (85.9); 76.0%-92.2%	67 (63.2); 53.7%-71.8%

[a]SC: symptom checker.

Usefulness of SCs

Of the 71 users, 29 (40.8%) considered SCs (rather) useful, while 18 (25.4%) found them (rather) not useful. The remaining one-third of participants (24/71, 33.8%) reported that SCs were sometimes useful and sometimes not useful to them.

Between users considering SCs useful and those who did not (disregarding those who found them sometimes useful and sometimes not), all sociodemographic variables except for age revealed differences; see Table 5. In our sample, males were 4 times (16:4) more likely than females (13:13; odds ratio [OR] 4.0) to rate their experience with SCs as useful. The difference in general usefulness was statistically significant (P=.002). A higher net household income was also strongly associated with usefulness (mean EUR 2591.63, SD EUR 1103.96 [mean US \$2798.96, SD US \$1192.28], among those considering SCs useful vs mean EUR 1626.60, SD EUR 649.05 [mean US \$1756.73, SD US \$700.97], among those who did not; P<.001). Additionally, a higher level of formal education was found among participants rating the usefulness of SCs favorably (55.2% vs 22.2% with a university or college degree; P=.016).

Higher self-efficacy scores were also associated with rating SC usage as useful: Visual analysis of the association between self-efficacy and usefulness hinted at a threshold effect; see Figure 2. Although users with a self-efficacy score above 3.5 commonly found SCs useful (25:10), users below this threshold did not (3:8; OR 6.6). Similarly, most participants (9:1) scoring very high (>5/6) on the ATI scale considered SCs useful, while the majority (3:4) of users with a low score (<3/6) did not. Mean and median scores for affinity for technology, however, were similar across these 2 groups (see Figure S1 in Multimedia Appendix 1). Although in lesser magnitude, these observations held when including participants rating their previous experience as "sometimes helpful, sometimes unhelpful."

Although users rating their experience as useful self-reported higher general health and lower restrictions for health reasons than users with unhelpful experiences with SCs, these findings were not statistically significant and had a small effect size. Rates of all 3 indicators of health care usage (inpatient hospital stay within the past year, number of physician visits within the past year, currently undergoing psychotherapy) were higher among participants considering SCs useful. In contrast, users currently suffering from panic or anxiety disorder more commonly considered SCs not useful than useful (see Table S4 in Multimedia Appendix 1).

Although the usage of other health apps in general was strongly associated with the awareness and usage of SCs, it was not associated with considering SCs useful.

Table 6 summarizes the gender distribution of participants who were aware of SCs, used them, and considered them useful: women seemed to know and use SCs more frequently. However, the proportion of users among those who knew about SCs was similar for men and women, but men found SCs more commonly useful.

Table 5. Characteristics of and interindividual differences between users considering SCs[a] useful and not useful.

Characteristics	Considered SCs useful	Considered SCs sometimes useful, sometimes not	Did not consider SCs useful
Participants, n (%); 95% CI	29 (40.8); 29.3%-53.2%	24 (33.8); 23.0%-46.0%	18 (25.4); 15.8%-37.1%
Gender, n (%); 95% CI			
Male	16 (55.2); 41.4%-75.8%	6 (25.0); 12.5%-43.9%	4 (22.2); 5.6%-42.4%
Female	13 (44.8); 31.0%-65.5%	18 (75.0); 62.5%-93.9%	13 (72.2); 55.6%-92.4%
Diverse	0 (0.0); 0.0%-20.6%	0 (0.0); 0.0%-18.9%	1 (5.6); 0.0%-25.7%
Education, n (%); 95% CI			
No school diploma	0 (0.0); 0.0%-19.7%	0 (0.0); 0.0%-22.3%	0 (0.0); 0.0%-27.7%
Primary school/lower secondary school	2 (6.9); 0.0%-26.6%	1 (4.2); 0.0%-26.45%	1 (5.6); 0.0%-33.2%
Secondary school leaving certificate	4 (13.8); 0.0%-33.5%	3 (12.5); 0.0%-34.8%	0 (0.0); 0.0%-27.7%
A level/high school diploma	3 (10.3); 0.0%-30.1%	5 (20.8); 4.2%-43.1%	6 (33.3); 16.7%-61.0%
Completed vocational training	4 (13.8); 0.0%-33.5%	5 (20.8); 4.2%-43.1%	7 (38.9); 22.2%-66.5%
University or college degree	16 (55.2); 41.4%-74.9%	10 (41.7); 25.0%-64.0%	4 (22.2); 5.6%-49.9%
Monthly net household income (EUR/US $[b]), mean (SD)	2591.63 (1103.96)/2798.96 (1192.28)	2273.47 (1054.62)/2455.35 (1138.99)	1626.60 (649.05)/1756.73 (700.97)
Self-efficacy, mean (SD)[c]	4.21 (0.66)	4.07 (0.48)	3.63 (0.81)

[a]SC: symptom checker.

[b]EUR 1.00=US $1.08.

[c]On a scale of 1-5.

Figure 2. Self-efficacy by usefulness rating. Above a certain threshold of self-efficacy, users are about equally likely to rate the app as useful or not useful, but below that threshold, they commonly find it unhelpful.

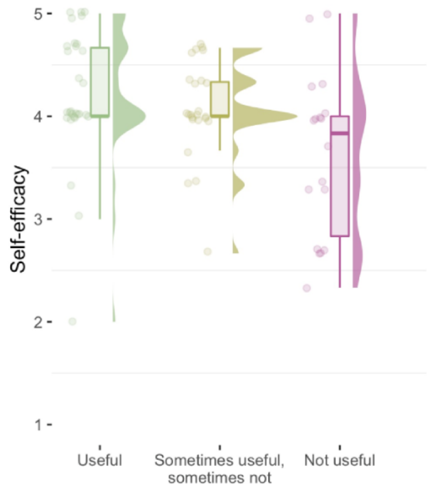

Table 6. Gender[a] distribution of those knowing about SCs[b], using them, the proportion of users among those knowing about them, and their usefulness rating.

Subgroup	Male	Female
Know about SCs, n/N (%)	69/521 (13.2)	107/560 (19.1)
Use SCs, n/N (%)	26/521 (5.1)	44/560 (7.7)
Proportion of users among people knowing about SCs, $n_{User}/n_{Knowing}$ (%)	26/69 (37.7)	44/107 (41.1)
Proportion of users finding SCs either “rather useful” or “very useful,” n_{useful}/n_{users} (%)	16/26 (61.5)	13/44 (29.6)

[a]Due to the low sample size (n=3, 0.3%), participants of a diverse gender are not reported here.

[b]SC: symptom checker.

Discussion

Principal Findings

Prevalence of SC Usage

Our cross-sectional survey found that only a minority of 16.3% of German people with internet access are aware of SC apps, and among them, only a minority of 40.1% report having used SCs at least once before. Thus, we find the proportion of SC users among the German online population to be lower (6.5%) than the figure of diagnostic app users (13.0%) previously reported [58].

The low prevalence of SC usage suggests that the current users are “innovators” and “early adopters,” as defined by diffusion of innovation theory [59].

Misalignments in Subgroups

Comparing subgroups of participants, we identified sociodemographic and other interindividual characteristics associated with knowing about and using SCs and considering them useful. Taking these findings together, our study hints at some misalignments between factors associated with using and benefiting from SCs, that is, there are some groups that might potentially benefit from these tools but are less inclined to use them and others that are inclined to use them but often do not benefit from them (eg, those with panic or anxiety disorder).

Gender

A prime example of this misalignment in our data is gender: our study concurs with previous research that women more commonly use SCs than men [19,20]. At the same time, men who are aware of SCs are about equally likely to use SCs as women, which concurs with the Healthwatch Enfield study [22]. Taken together, this suggests that this gender gap is not due to dissimilar conversion rates.

Similarly, gender-specific differences in the perception of the usefulness of SCs do not seem a plausible driver of unequal gender usage either, as among users, men more commonly reported considering SCs useful than their female counterparts. Thus, the disparity in the awareness of SCs between men and women might be the primary cause behind the gender gap in usage. A multitude of reasons might explain that effect: Women are more often responsible for care work [60] and, therefore, potentially more likely to search for online health information on someone else’s behalf. Women may also seek health information more often (and find SCs) because of higher health anxiety [61]. Third, advertisements from SC developers might be directed more toward women than men.

Due to the small sample size of SC users, we can only speculate as to why men more often considered their usage to have been helpful: As previously published studies suggest men being less risk-averse than SCs (and women) regarding triage decisions [17,62], a differing second opinion might be considered more useful than a confirmative one. Additionally, as women are more inclined to inform themselves about symptoms, health topics, and the health care system [63-66], the additional benefit from SCs might be less pronounced.

Age

Regarding age, we found a similar pattern as for gender. Although SC users were younger than nonusers (in line with previous research [18-20,23]), we found no association between age and the inclination to use SCs in the group that was aware of SCs, in contrast to the Healthwatch Enfield study [22]. Furthermore, age was not associated with perceived usefulness, as reported elsewhere [19]. Thus, older patients may also benefit from SCs when informed about these tools. As the amount of care required increases with age [67], the potential of SCs for older patients and how they can become aware of them should be a priority for further investigation.

Education

Like other studies [20,34], we found SC users to have a high level of formal education. Formal education followed a comparable pattern as age and gender: Participants with higher levels of formal education were more commonly aware of SCs, but once participants were aware, the level of education did not influence the inclination to use or self-reporting of benefits from SCs.

Income

Factors showing relevant but distinct patterns were income, health-related variables, affinity for technology, and self-efficacy. A higher income was associated with both a higher awareness of SCs and greater perceived usefulness. Although the higher awareness might again be a result of the marketing strategy of SC developers, the limited number of SC users in our sample allows no conclusive argumentation as to why higher-income users reported to benefit more from SCs. As income is a function of a combination of different socioeconomic factors and interindividual traits, higher-income users might approach SCs for different reasons and with different expectations than lower-income users.

Health Status

Concerning health-related variables, prior usage of health apps correlates highly with the awareness of SCs and the inclination to use them but is not a predictor of finding the usage beneficial. Thus, akin to age, gender, and formal education, people previously unaware of health apps might benefit from them once they are aware of them. Because SC users commonly tend to be younger, have a high income, and are well-educated individuals, one may conclude that SCs cater to a healthier subgroup of the population. However, our findings show no such health gap: users and nonusers appraised their self-reported general health level equally. The reported restrictions in daily life due to health-related issues is greater among users than nonusers, and in particular, the burden of mental illness is much greater on users compared to nonusers. However, greater usage does not translate into higher perceived usefulness: participants considering SCs useful were more commonly the healthier users and especially less often users reporting to suffer from mental health problems or undergo psychotherapy. The high burden of mental health issues among users highlights the importance of studying the effects of mental health on usability, perceived usefulness, and risks of SC usage.

Affinity for Technology Interaction and Self-Efficacy

An affinity for technology interaction increased the likelihood of knowing about SCs and finding them useful, but it had no effect on the intention to use SCs. Lastly, higher self-efficacy was associated with a greater likelihood of finding SCs useful but not with knowledge about them or the intention to use them. The visual inspection of the data leads us to hypothesize a nonlinear relationship between an affinity for technology interaction, self-efficacy, and considering SCs useful: Individuals below a certain threshold of self-efficacy (which is situated below the population's average score) might likely not report finding such tools useful. In contrast, individuals above a certain threshold of affinity for technology (which is situated far above the population's average score) are highly likely to consider SCs useful.

Limitations

We used a sample stratified by gender, state of residence, net household income, and age. However, since we used an online questionnaire, there was a risk of selection bias—choosing people who had a higher affinity for technology than the general population. Franke et al [46] found differences in the affinity for technology between samples recruited online and offline in a validation study. A university and social media sample had a mean affinity for technology of 4.14, while a random sample in German cities (using pen and paper) had a mean affinity for technology of 3.58. Our study sample's average ATI score was 3.74 and thus slightly higher than expected for a random sample among both "offliners" and "onliners." As most of our participants (>91.9%) indicated using the internet multiple times a day, we certainly missed the population subgroup with low technological affinity.

Although the sample size was suitable for the aim of this work, the subsets of those aware of and those using SCs were rather small. Thus, we might have missed important associations of a smaller effect size and overestimated the degree of other associations by chance. Due to the nature of exploratory analyses, which investigate a multitude of associations at once, our findings are subject to the multiple testing problem. However, we conducted robustness checks correcting *P* values. Although we replicated findings from previous studies (eg, users being more often female, younger, and well educated), other results, such as men finding SCs more useful than women, need to be replicated in future studies. Especially, the hypotheses we derived from the presented findings must be replicated in further studies—for example, that a lack of awareness is the driver behind people's intention to use SCs, rather than sociodemographic differences.

Our data stem from a cross-sectional online survey of the German population. Thus, all the data are self-reported data. Especially concerning mental health, we might have missed participants with a mental illness who are not open to reporting this in a survey.

As a final point, we evaluated only the subjective usefulness of SCs, not their objective usefulness (eg, facilitating safer, more informed decision-making and guiding users toward appropriate health care facilities). SCs were, for example, perceived as more useful by men, but whether they led to better decisions or other favorable outcomes remains unproven.

Conclusion

Our findings hint at a misalignment between factors associated with using and benefiting from SCs. That is, some groups could potentially benefit from these tools but are uninclined to use them or are unaware of them, while other groups could be inclined to use SCs but seem to not benefit from them. Based on these observed misalignments, our data suggest that SCs currently fail to alleviate inequalities in access to health care despite their high availability and convenient service: Users with higher educational levels, income, and self-efficacy are more likely to report benefiting from SCs, while users with lower self-reported health and mental health issues are less likely to do so. Simply expanding the awareness of SCs among the general population to reduce unequal awareness and unequal usage might leave this unequal distribution of benefits intact.

Ultimately, how the outlined misalignments between using and benefiting from SCs will evolve when a greater part of the general population becomes familiar with SCs and decides to use them remains an open question.

Our findings provide some indication that SCs' full potential—in terms of users considering them useful—might be tapped by the majority and late adopters (ie, those adopting an innovation after the commonly younger and more educated [68,69] innovators and early adopters). However, health variables unrelated to the inclination to adopt technology early—such as the specific medical concern, past medical history, and the context an SC is approached with—are associated with perceived usefulness and might be a bigger factor influencing whether an SC offers its user a valuable service. To get consumers and patients who are more likely to benefit from SCs to use them, they must have a low-barrier point of contact in the patient journey. Thus, integrating them into the standard health care system might prove a more fruitful path forward than simply promoting (or discouraging) the stand-alone use of such apps.

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Conflicts of Interest

MK, HN, DF, FB, and MLS previously received funding from the German Federal Ministry of Health. FB reports grants from the German Federal Ministry of Education and Research, the Berlin Institute of Health, the Hans Böckler Foundation, the Robert Koch Institute, the Einstein Foundation, and the Berlin University Alliance and personal fees from Elsevier Publishing, Medtronic, and GE Healthcare outside the submitted work. MK, HN, and MLS invest in exchange-traded funds that hold shares of various companies in the technology and healthcare sectors. These companies do not gain financially from the publication of this article, but might do so in the future. MLS was an employee at Ada Health GmbH (formerly known as medx GmbH), the developer company of a symptom checker application during 2014 and 2015. DF received funding from the German Ministry of Education and Research, the European Commission Horizon Europe Program, and the Einstein Foundation.

Multimedia Appendix 1

Full tables and additional analyses.
[DOCX File , 247 KB-Multimedia Appendix 1]

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Abbreviations

ATI: Affinity for Technology Interaction
OR: odds ratio
SC: symptom checker

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