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# Potentials and Pitfalls of Self-Help Tools: A Survey Study of Digital Psychiatry in Denmark

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## Abstract

Welfare systems around the world are struggling to cope with the growing number of people needing psychiatric care. Consequently, digitalization has become a beacon of hope, making treatment more accessible and bolstering patient empowerment. However, scholars have shown that digital divides prevail. This study examines the social sustainability of digital psychiatry by illuminating patient perspectives on mental health digital solutions (MHDS) in Denmark. This is done via a unique survey sample from register data of 1,478 adults in psychiatric treatment in 2023. First, the study examines the association between seven predictors—socioeconomic position, severity of mental illness, age, gender, geographic location, migrant status, and social support—and MHDS usage via binary logistic regression analysis. The analysis reveals a social stratification behind the usage of MHDS. Second, the study conducts two latent class analyses—one for MHDS users and one for non-users—to identify underlying groups that characterize patient perspectives on MHDS. For the users, the analysis reveals latent classes characterized by experiences of participation as well as isolation. For the non-users, the analysis highlights latent classes characterized by few barriers to using MHDS as well as by multiple barriers related to the limited affordances of MHDS. Lastly, the study uses multinomial logistic regression analysis to examine the association between the predictors and the latent classes, showing that latent class membership has a social component. Taken together, the findings indicate that social and digital inequalities are intertwined. To become socially sustainable, digital initiatives should complement, and not replace, in-person treatment.

## Keywords

digital divide; digital inclusion; digitalization; empowerment; psychiatry; participation; welfare state

## 1. Introduction

Mental health has been declared a pressing and ubiquitous issue worldwide. One key solution advocated by the World Health Organization (2021), as well as national and local services, is the use of mental health digital solutions (MHDS). These solutions are supposed to create more cost-efficient, accessible, and personalized treatment for psychiatric patients while also reducing pressure on welfare professionals. We have thus seen a proliferation of MHDS in recent years.

On the one hand, MHDS can be considered a lever for patient empowerment, because they allow patients to access information about their treatment, monitor their symptoms, and communicate with welfare professionals across time and space (Berrouiguet et al., 2018; Carpenter-Song et al., 2022; Cheng et al., 2021; Vitger et al., 2021). On the other hand, existing research shows that digital divides and inequalities prevail (Buchert et al., 2022; Eubanks, 2007; Reisdorf & Rhinesmith, 2020; Schradie, 2020), and that individuals with mental illness are more likely to have limited access, skills, and desire when it comes to using technology (Borzekowski et al., 2009; Comber et al., 1997; Dobransky & Hargittai, 2016; Ennis et al., 2012; Li & Kirkup, 2007; Tobitt & Percival, 2019; Wang et al., 2011; Wong et al., 2020). Scholars suggest that MHDS can exclude patients who do not have the means to use technology or need intensive psychiatric care (Greer et al., 2019; Robotham et al., 2016). Consequently, MHDS can be seen as a double-edged sword, carving channels for both social inclusion and exclusion.

Seen through a critical lens, MHDS are the result of a neoliberalization of welfare, where participation and responsibility are two sides of the same coin. In this way, MHDS evoke self-help and rest on the notion of an actively participating patient (Lupton, 2013, 2014). This study examines how this notion of participation can be empowering for some groups of patients while potentially excluding others. Thus, the study is governed by a two-fold research question: First, what characterizes psychiatric patient groups in terms of their experiences with and attitudes toward MHDS? Second, how are these experiences and attitudes related to social inequalities?

The first part of the research question is examined via two latent class analyses (LCAs). One of the LCAs uncovers patient groups in terms of experiences with using MHDS, while the other LCA sheds light on patient groups in terms of reasons for not using MHDS. Empirically, the LCAs are based on a large survey among psychiatric patients in Denmark investigating patient experiences with and attitudes towards MHDS. The survey is based on access to unique Danish register data, providing a representative gross survey sample. This access to register data is a remarkable strength of the study, bolstering the external validity of the findings.

The second part of the research question is investigated via regression analyses. As a preliminary analysis, the article examines the association between seven predictors—socioeconomic position, severity of mental illness, age, gender, geographic location, migrant status, and social support—and usage of MHDS. This provides insights into the differentiating mechanisms behind MHDS usage. Subsequently, the article conducts two multinomial logistic regression analyses examining whether the predictors are associated with latent classes from the LCAs and thus create unequal conditions in experiences and attitudes.

In contrast to much of the existing literature in clinical psychology and psychiatry (see e.g., Andersson et al., 2019; Barak et al., 2008; Batra et al., 2017; García-Lizana & Muñoz-Mayorga, 2010; Hayes et al., 2016; Hubley et al., 2016; Yellowlees et al., 2021), this study does not focus on the treatment effects of MHDS. Instead, it complements the existing literature by providing a sociological perspective on the ambiguity of participation and responsibilization that MHDS instigate.

## 2. Scholarship on Empowerment

This study uses empowerment as an overall analytical perspective. Empowerment plays a central role in welfare literature and has a multifaceted and ambiguous meaning (Frank & Bjerge, 2011). Some seminal definitions suggest that empowerment is related to feeling competent and willing to take action (Zimmerman & Rappaport, 1988). Similarly, Arnstein's (2019) ladder of participation depicts empowerment as an ascending journey from dependence and coercion to agency and autonomy.

Scholars have examined how the call for user empowerment and participation alters the conventional hierarchy between welfare professionals and welfare users. It is suggested that the call for user participation promotes user expertise and challenges professional authority (Järvinen & Kessing, 2021; Schneider-Kamp & Askegaard, 2020). Welfare professionals are no longer called to prescribe the course of action, but should instead guide welfare users in self-management (Greenhalgh, 2009). This proves a difficult balance for welfare professionals: On the one hand, they must endorse the individual autonomy of welfare users; on the other hand, they must provide support that is consistent with auditing goals (Järvinen, 2016).

The multifaceted nature of empowerment means that it can become a vessel for different, sometimes even contradictory, political agendas (Andersen & Elm Larsen, 2011; Mayo et al., 2004). In this way, empowerment is a normative concept. Some critical scholars suggest that empowerment understood as self-help is a neoliberal way of individualizing social problems (Bjerge, 2007; Bjerge & Nielsen, 2014; Oute et al., 2015). Paradoxically, empowerment can then lead to exclusion. This happens when individuals who fail to live up to the imperative of helping themselves are excluded from welfare services because their problems are considered self-inflicted (Howell & Voronka, 2012; Mik-Meyer, 2017; Ringø et al., 2017). In the area of psychiatry, scholars criticize the prevailing recovery model for responsibilizing psychiatric users to get better and obey prescriptive standards of normality (Jørgensen et al., 2020; Oute & Ringer, 2014; Rizq & Jackson, 2019; Speed, 2011).

At the same time, empowerment can be seen as a way of addressing social injustice by giving voice to the users of psychiatric services. As highlighted by prominent critic of the psy-disciplines Nikolas Rose (N. Rose, 2018), psychiatry allows coercion and force if psychiatric patients are deemed at risk of harming themselves or others. Historically, mental illness has been used to denounce and silence the voices of patients. To counter this "epistemic injustice," Diana Rose and Nikolas Rose argue that we must attribute intrinsic value to the lived experiences and embodied expertise of psychiatric patients (D. Rose & Rose, 2023, p. 46).

"Nothing about us without us" is the slogan of mental health and disability empowerment activism (Charlton, 1998, p. 4). This call for participation and involvement can be seen through at least two lenses. On the one hand, calling for participation may be no different from calling for self-help, neglecting the power relations and coercion that hinder participation. On the other hand, participation can be a lever for freedom, autonomy, and agency. This study examines the heterogeneous effects of empowerment initiatives like MHDS across different patient groups. In this way, it seeks to provide a nuanced perspective on empowerment and MHDS, highlighting impediments to socially sustainable psychiatry.

## 3. Psychiatric Welfare Services in Denmark

Denmark has a universal welfare system that provides free access to social and health care services. However, the Danish welfare system is increasingly marked by inequalities related to the liberalization of welfare services. For instance, there is a rapid growth in supplementary private healthcare insurance, constituting a reduction in the universality of healthcare services (Greve, 2020). Individuals with private insurance have faster and better access to healthcare compared to individuals without. This access inequality is particularly salient in terms of psychological counseling (Greve, 2020, p. 140). Individuals without private insurance must either pay a substantial amount of money for psychological counseling or present with an acute, severe condition that qualifies for public psychiatric treatment. Even though public psychiatric services in Denmark solely treat severe mental illnesses, they nevertheless suffer from long waiting lists and scarce resources.

Scholars have shown a growing discrepancy in life expectancy across different socioeconomic and demographic groups (Brønnum-Hansen & Baadsgaard, 2012) and a corresponding inequality in terms of public health outcomes (Dybbroe, 2020). This is particularly salient in terms of psychiatric patients, who are statistically considered to be some of the most vulnerable groups in society. Studies have shown that psychiatric patients have excess mortality (Kugathasan et al., 2019; Nordentoft et al., 2013; Plana-Ripoll et al., 2020), possibly related to the increased risk of developing further diseases (Ribe et al., 2014) and the risk of worse healthcare treatment than the average population (Davydow et al., 2015, 2016; Graversen et al., 2021). In other words, Denmark's *de jure* equal access to healthcare is far from *de facto* equal access, and the association between digitalization and healthcare inequalities examined in this study is therefore relevant for other countries.

Denmark proves an interesting and relevant case for examining inequalities in relation to digitalization because the Danish healthcare sector is highly digitalized in general (Schmidt et al., 2019). The Danish psychiatric sector is currently undergoing an expansive reform as a response to the growing need for psychiatric care. This includes budget increases and changes to the way the sector is organized. Here, MHDS are an integral part of the reform, suggesting that MHDS will become a pivotal part of Danish psychiatry in the future (Indenrigs- og Sundhedsministeriet, 2023). Thus, it is salient to examine the potentials and pitfalls of MHDS that are expanding in Denmark in a time of growing global interest in digitalized welfare services.

## 4. Empirical Material and Data Collection

### *4.1. Questionnaire*

The study was approved by the Institutional Review Board at Aarhus University (approval code: BSS-2023-084). It was preregistered before data collection on October 12, 2023, using OSF registers (https://osf.io/a8xyu/?view_only=e3b4ef242f8b4ce59bf4483c981a3401). Please note that there have been minor, non-substantive alterations. The concepts of responsibilization and self-technologies are not directly used as dependent variables in the LCA. The operationalizations of the predictors severity of mental illness and geographical location are also altered slightly, as shown in Supplementary File 1. In the test for representativeness, the study solely uses $\chi^2$ goodness of fit tests and follows the conventional $p < 0.05$. Lastly, the study does not include an interaction term between socioeconomic position and severity of mental illness because of multicollinearity.

The study is based on a survey among patients who in 2023 were in either inpatient or outpatient psychiatric treatment in Denmark. The questionnaire inquires about the overall use of technology and perspectives on MHDS. Then, the questionnaire asks whether the participants have used MHDS. Those who have used MHDS receive questions about their experience. Those who have not used them are asked why not and about motivational factors. The full questionnaire is available in Supplementary File 2.

Some of the questionnaire items are inspired by international survey studies with a similar target group (Bonet et al., 2018; National Alliance on Mental Illness, 2014) and were translated into Danish by the author. The remaining questionnaire items are designed specifically for this study. The questionnaire has been validated by professionals at the Center for Digital Psychiatry in the Region of Southern Denmark, who are experts in communication with psychiatric patients. They provided crucial feedback on sentence structure, word choice, and other linguistic aspects. As another way of ensuring measurement validity, the study began with a pilot testing phase. The author and a research assistant conducted cognitive interviews with nine individuals who recently had been or were currently in psychiatric treatment. Since the questionnaire varies depending on whether the respondents have used MHDS, the questionnaire was tested on both groups. Participants listened to each survey item read out loud and were then asked to "think out loud," reasoning their response. The questionnaire was revised after the pilot phase, correcting ambiguous or misleading formulations.

### 4.2. Population and Sample

Based on simple random sampling selection, the survey was distributed to 7,000 patients. The gross sample came from the Danish Health Data Authorities. As an inclusion criterion, participants were required to have had at least one contact with Danish psychiatry in the period of January 1, 2023–November 11, 2023, with a psychiatric working diagnosis according to the 2019 version of the ICD-10 diagnosis classification manual (World Health Organization, 2019). Participants were also required to be 18 years or older. Excluded from the sample were participants with diagnoses classified as mental retardation, F71*–F73* according to the 2019 version of the ICD-10 diagnosis classification manual (World Health Organization, 2019), as well as legally incompetent participants, individuals living outside of Denmark at the data extraction time, and individuals under name and address protection.

Uniquely, the study has access to information about the whole population of psychiatry users. This register data from the Danish Health Data Authorities enables us to render the gross sample representative of the population of psychiatry users in Denmark. Additionally, the study employs register data from Statistics Denmark, providing highly reliable socioeconomic and health information about the population of psychiatry users. We are thus able to avoid the problems of missing data and fallacies of self-reporting that most other survey studies face.

### 4.3. Data Collection Approach

Psychiatric patients are a hard-to-reach population. Therefore, rather than relying solely on Computer-Assisted Web Interviewing (CAWI), the study used a host of different survey approaches to increase the response rate. The survey was primarily sent out as an official digital mail, supplemented with Paper-and-Pencil Interviewing (PAPI) for the 11% of the gross sample who were exempt from receiving digital mail. Further, patients received SMS reminders and digital mail reminders. Lastly, the study used Computer-Assisted Telephone Interviewing (CATI) with patients who had an available telephone number. PAPI and CATI are known to be costly and highly laborious in comparison to CAWI, but they are also known to be the most effective ways of contacting hard-to-reach populations (Kagerbauer et al., 2013). Additionally, PAPI and CATI ensured that patients facing digital difficulties had the opportunity to participate. The data were collected over a two-month period between December 28, 2023–February 28, 2024.

The survey obtained 1,478 full responses and had a response rate of 21.1%. Because this population is considered hard to reach, this is deemed a favorable response rate. Importantly, 103 partial responses, or 1.5% of the gross sample, were excluded from the analysis. Most of the partial responses had only responded to the initial items without completing the rest of the questionnaire.

## 5. Method

The statistical analysis consists of three parts. First, binary logistic regression analysis is used to examine the association between MHDS usage and key predictors. Second, LCA is used to identify underlying groups that characterize participants' experiences of and attitudes toward MHDS. Third, the study employs multinomial logistic regression to examine the association between the latent classes and key predictors.

LCA is a statistical method used to identify underlying subgroups within a set of observed categorical variables. It assumes that these subgroups, or latent classes, explain the variation in the observed data. LCA is a person-oriented approach examining qualitative characteristics on a large scale (Collins & Lanza, 2010) and is a particularly useful method for uncovering heterogenous vulnerabilities (T. Rose et al., 2017; Scotto Rosato & Baer, 2012) and subgroups that would benefit from a particular intervention (Weller et al., 2012). Thus, LCA is a well-suited method for this study, because it enables a nuanced account of different groups of patients and their perspectives on MHDS. In this case, the assumption is that the latent classes explain the variation in participants' experiences and attitudes. Hence, the analysis consists of two LCAs: one for participants who have used MHDS and one for participants who have not. Both LCAs are carried out via the statistical software program Stata using the LCA Stata plugin (Lanza et al., 2018).

There are different information criteria (IC) to evaluate the model fit and thus determine the number of latent classes. In this study, the model fit is assessed via the Bayesian information criterion (BIC), the sample-size-adjusted Bayesian information criterion (*a*BIC), and the Akaike information criterion (AIC). Lower values entail better model fit. However, if the IC point in different directions, the best model fit is determined based on the BIC, which is often deemed superior to the other IC (Collins & Lanza, 2010; Nylund et al., 2007; Vermunt, 2002). In addition, this study reports entropy, which can be used as a diagnostic criterion showing how well the model characterizes the latent classes. Values close to 1 are ideal (Celeux & Soromenho, 1996), but there is no official cutoff point.

LCA conventionally employs maximum likelihood estimation to estimate model parameters. Key parameters are the latent class prevalences and the item response probabilities. The latent class prevalences indicate the size of each latent class in the population. The latent classes are mutually exclusive and exhaustive, meaning that everyone in the population will be assigned to a class based on probabilistic assessment. The item response probabilities indicate the conditional probability of observing a particular response pattern given latent class membership. A central part of the analysis is to name and characterize the latent classes based on the item response probabilities (Collins & Lanza, 2010).

In the subsequent multinomial logistic regression analyses, modal assignment is used to determine the best class match for each individual based on the posterior probabilities using the LCA Stata plugin (Lanza et al., 2018). For all the regression analyses, statistical significance is determined via $p < 0.05$.

## 6. Concepts and Measurement

### *6.1. Digital Psychiatry*

MHDS are part of the movement towards digital psychiatry. However, there is no official definition of digital psychiatry, and the concept has been defined in a variety of ways (Bucci et al., 2019; Golinelli et al., 2020; Stern et al., 2023). In this study, digital psychiatry is seen as a broad concept spanning telemedicine (technology-mediated consultations), eHealth (online health promotion and treatment), mHealth (mobile health technology), and algorithm-based medicine (use of algorithms and big data for health promotion and treatment; Marent & Henwood, 2022).

This study draws on the definition offered by Legind et al. (2022), who adapt Topol's (2019) definition of digital psychiatry to a Danish context. Specifically, digital psychiatry includes video consultations, apps, sensor technology, online therapy, artificial intelligence, and virtual reality. Based on the World Health Organization's (2018) taxonomy of digital health technologies, digital psychiatry is understood as a form of intervention—that is, it intervenes in the patient's life to instigate change. Therefore, activities like ordinary internet searches, podcasts, and videos on YouTube are not part of the concept of digital psychiatry.

### *6.2. Empowerment*

Measuring empowerment in relation to MHDS, this study builds on an empowerment survey consumer-constructed scale, specifically focusing on the dimensions of self-efficacy/self-esteem, power/powerlessness, community activism/autonomy, and optimism/control over the future (Cottrell & Langzettel, 2005; Rogers et al., 1997). In a similar vein, the study draws on the first subscale of the Health Care Empowerment Scale, which consists of being informed, committed, collaborative, and engaged (Johnson et al., 2012). However, the specific operationalizations of empowerment have been specifically designed for this study, because no other studies have operationalized empowerment in relation to MHDS. For the MHDS users, empowerment is measured via nine Likert scale items:

- I have felt left to myself when using digital tools.
- Digital tools have given me a better understanding of my mental health.
- Overall, I have benefited from using digital tools.
- Digital tools have made it easier for me to manage on my own in my daily life.
- Digital tools have made it easier to determine where and when my treatment should take place.
- I have only used digital tools because there were no other treatment options.
- Digital tools have made it easier to get information about my treatment options.
- Because of digital tools, I need less contact with my welfare professional.

- Digital tools have made me more aware of my symptoms.

For the non-users, the focus is on the perceived barriers to using MHDS based on six dummy scale items:

- I do not have access to necessary IT devices (e.g., computer or phone).
- I do not want to use more IT devices in my daily life (e.g., computer or phone).
- I do not think it is as beneficial as meeting in-person with my welfare professional.
- I do not think I have the right technical skills.
- I do not trust the data security.
- I do not know which tools are available.

### 6.3. Socioeconomic Position

The study is based on the materialistic dimension of socioeconomic position. Consequently, it does not capture the symbolic dimension (Krieger et al., 1997) or the subjective dimension (Diemer et al., 2013) of socioeconomic position. The study draws inspiration from Duncan's index of socioeconomic inequality (Stevens & Featherman, 1981), albeit without the income dimension since this indicator is presumed to correlate strongly with education and employment status. Socioeconomic position is measured via register data from Statistics Denmark about labor market position and highest educational attainment. Supplementary File 1 shows an elaborate description of each register and each register variable used in the study. Socioeconomic position is calculated as an index between labor market status and highest educational attainment, where the two dimensions are given equal weight. Labor market position is based on data from December 31, 2022, and educational attainment is based on data from September 30, 2022, due to register data availability. However, socioeconomic position is considered a relatively stable social phenomenon. Therefore, the time difference should not significantly influence the results.

### 6.4. Severity of Mental Illness

Severity of mental illness describes how pervasive and potentially disabling an individual's mental illness is. In line with other studies (Ruggeri et al., 2000), this study defines severe mental illness as diagnoses with psychotic symptoms, that is F20–F22*, F24*, F25*, F28–F31*, F32.3*, and F33.3*, according to the 2019 version of the ICD-10 diagnosis classification manual (World Health Organization, 2019). Severity of mental illness is a multifaceted concept, and a limitation of the present study is that it does not focus on the duration of illness or functional impairment (National Institute of Mental Health, 1987). Severity of mental illness is measured via register data from the Danish Health Data Authorities. A participant is considered to have severe mental illness if they have at least one registration of the mentioned diagnoses in the period January 1, 2023–December 15, 2023.

### 6.5. Social Support

Social support is defined as the social resources that an individual has available or assumes they have available in formal or informal contexts that are not provided by welfare professionals (Cohen et al., 2001). In this way, it relates to cognitive and bonding social capital (Harpham et al., 2002). Barrera (1986) introduces three distinct dimensions of social support, namely embedded, perceived, and enacted social support. The first is related to the magnitude and quality of an individual's social network; perceived social support refers to how much support an individual presumes to have available in their network; and enacted social support refers to how much support the individual receives from their network (Barrera, 1986). In this study, embedded and perceived social support are examined building on the work of Krause (1999). Enacted social support is investigated by drawing on the Inventory of Socially Supportive Behaviors (Barrera & Baca, 1990). Social support is measured via the survey questionnaire as an index where each dimension is given equal weight.

The remaining predictors—gender, geographical location, migrant status, and age—are from June 30, 2023. The former three consist of binary outcomes, while the latter represents the participant's actual age.

## 7. Contextual Analysis of MHDS in Psychiatry

### *7.1. Distributions and Representativeness*

Table 1 shows the distributions of each register predictor in the population as well as in the gross and net samples. As previously mentioned, the gross sample was statistically representative of the population using simple random sampling selection. The net sample is not representative of all parameters because of low response rates for certain groups.

**Table 1.** Distributions in population, sample, and test for representativeness.

| Predictors | Population | Gross sample | Net sample |
|---|---|---|---|
| Age | | | |
| 18–27 years | 28.6% | 28.7% | 23.8% |
| 28–37 years | 23.3% | 23.2% | 19.4% |
| 38–47 years | 15.1% | 15.0% | 16.3% |
| 48–57 years | 13.2% | 13.5% | 18.7% |
| 58+ years | 19.9% | 19.6% | 21.7% |
| Total | 100% (89,266) | 100% (6,995) | 100% (1,477) |
| Gender | | | |
| Male | 42.8% | 42.4% | 37.9% |
| Female | 57.2% | 57.6% | 62.1% |
| Total | 100% (89,266) | 100% (6,995) | 100% (1,477) |
| Migrant status | | | |
| Non-Danish | 14.1% | 14.1% | 9% |
| Danish | 85.9% | 85.9% | 91% |
| Total | 100% (89,266) | 100% (6,995) | 100% (1,477) |
| Geographical location | | | |
| Small city | 55% | 54.5% | 57.3% |
| Large city | 45% | 45.5% | 42.7% |
| Total | 100% (89,266) | 100% (6,995) | 100% (1,477) |

**Table 1.** (Cont.) Distributions in population, sample, and test for representativeness.

| Predictors | Population | Gross sample | Net sample |
|---|---|---|---|
| Severity of mental illness | | | |
| Non-severe | 66.3% | 65.5% | 67.7% |
| Severe | 33.7% | 34.5% | 32.3% |
| Total | 100% (89,371) | 100% (7,000) | 100% (1,478) |
| Socioeconomic position | | | |
| Low | 34.8% | 34.8% | 23.9% |
| Average | 42.9% | 43.7% | 48.2% |
| High | 22.3% | 21.5% | 27.9% |
| Total | 100% (87,495) | 100% (6,870) | 100% (1,467) |

Notes: Different totals are due to a lack of information at the register status time; for statistical purposes, the continuous variables socioeconomic position and age have been recoded as categorical variables; statistically significant $p$-values = the sample is significantly different from the population; age: $\chi^2 = 59.48$**; socioeconomic position: $\chi^2 = 80.59$**; gender: $\chi^2 = 14.58$**; migrant status: $\chi^2 = 31.17$**; geographical location: $\chi^2 = 3.23$; severity of mental illness: $\chi^2 = 1.16$; * $p < 0.05$, ** $p < 0.001$.

Table 1 shows that the net sample has an underrepresentation of young individuals, men, individuals with a low socioeconomic position, and individuals with a migrant background. However, the sample is representative in terms of geographical location and severity of mental illness. This means that the sample reflects the overall population in terms of the proportion of people with disorders featuring psychotic symptoms. The participants without severe mental illness are those with any other psychiatric disorder that, importantly, can still be experienced as strongly affecting their everyday lives.

### *7.2. Descriptive Findings*

We will first look at the descriptive features of the sample relevant for the statistical analyses. Table 2 shows the item responses for patients' overall usage of devices and their general opinion about MHDS. Table 2 shows that the participants seem to use technology in their everyday lives: 92.8% use a smartphone and 56.2% use a laptop computer. This is similar to the overall Danish population (Danmarks Statistik, 2020; Epinion, 2023). However, the participants do not seem to prioritize having the latest digital devices. Among some of the participants, there seems to be an understanding that MHDS are less desirable than meeting face-to-face with a welfare professional. Approximately half of the participants indicated a fear that MHDS will eventually come to replace face-to-face interactions with welfare professionals. Related to this, 59.5% of the participants state that the biggest downside of MHDS is that you are left to yourself to a greater degree. In turn, the biggest upsides to MHDS concern flexibility and outreach to people who live far away from psychiatric services. The reported upsides and downsides of MHDS can thus partly be seen as a reflection of the tension between individualized responsibility and freedom inherent in empowerment initiatives.

Crucially, Table 2 shows that MHDS are far from widespread among the participants: 60.8% of the participants have not used them, and only 33.2% have. As a precursor for the LCAs, it is salient to investigate whether there are statistically significant differences between the users and the non-users. This is done via binary logistic regression analysis assessing whether the predictors age, socioeconomic position, severity of mental illness, social support, geographical location, migrant status, and gender are associated with MHDS usage. Seeing it as a funnel, this preliminary analysis reveals differentiating mechanisms underlying the LCAs.

**Table 2.** Descriptive findings from the survey questionnaire.

| Items | Response categories | Percentages ($N$ = 1,478) |
|---|---|---|
| Have used MHDS | Yes | 33.2% |
| | No | 60.8% |
| | Do not know/Prefer not to answer | 6% |
| Daily use of IT devices (in general) | Smartphone | 92.8% |
| | Laptop | 56.2% |
| | Headphones | 55.6% |
| | Tablet | 30.3% |
| | Desktop computer | 23.6% |
| | Smartwatch | 16.2% |
| | Other | 7.2% |
| | Landline phone | 4.1% |
| | Not using devices | 1.3% |
| | Do not know/Prefer not to answer | 0.5% |
| Prioritize having the latest IT devices | Agree or strongly agree | 11.2% |
| | Neither agree nor disagree | 22.8% |
| | Disagree or strongly disagree | 63.9% |
| | Do not know/Prefer not to answer | 2.2% |
| Afraid that MHDS will replace in-person meetings with welfare professional | Agree or strongly agree | 50.5% |
| | Neither agree nor disagree | 18.8% |
| | Disagree or strongly disagree | 24.2% |
| | Do not know/Prefer not to answer | 6.4% |
| Biggest downside to MHDS | Left to yourself | 59.5% |
| | Requires access to devices | 13.7% |
| | Data security risks | 7.2% |
| | No downsides | 8.8% |
| | Do not know/Prefer not to answer | 10.8% |
| The biggest upside to MHDS | Flexible treatment | 30.9% |
| | Better outreach | 30.6% |
| | More autonomy in daily life | 13.1% |
| | No upsides | 11.3% |
| | Do not know/Prefer not to answer | 14.1% |

Notes: The participants could choose multiple options in the item "Daily use of IT devices (in general)," which is why the percentages do not sum to 100%; the items "Prioritize having the latest IT devices" and "Afraid that MHDS will replace in-person meetings with welfare professional" have been recoded from a five-category Likert scale to three categories; "Do not know" and "Prefer not to answer" were separate categories but are here coded together because the latter contains few responses (1–2% on each item).

### *7.3. Regression Analysis of MHDS Usage*

Table 3 shows the results of the binary logistic regression analysis of MHDS usage and the predictors. The number of observations differs from those presented in Table 2 because observations with missing values on any of the regression variables are excluded from the analysis. All continuous variables have been standardized. Non-use serves as the reference category.

**Table 3.** Binary logistic regression analysis with odds ratios for MHDS usage.

| Predictors | MHDS usage |
|---|---|
| Age | 0.71** |
| Socioeconomic position | 1.14* |
| Geographical location (ref. small city) | 0.77* |
| Gender (ref. male) | 1.38* |
| Social support | 1.19* |
| Migration status (ref. non-Danish) | 1.52 |
| Severity of mental illness (ref. non-severe) | 1.03 |

Notes: $N = 1{,}264$; Likelihood Ratio $\chi^2 = 59.63$**; log-likelihood = –794.34; * $p < 0.05$, ** $p < 0.001$.

The full model in Table 3 is significant ($p < 0.001$). The table shows that age is negatively associated with MHDS usage, meaning that younger people are more likely to use MHDS than older people. Interestingly, there is also a negative association between geographical location and MHDS usage, indicating that people from small cities are more likely to use MHDS than people from big cities. This could be related to the fact that MHDS include video consultations, which could be attractive for people who live far away from treatment facilities. As such, MHDS makes treatment more accessible by surmounting physical distances. Table 3 shows a positive association between socioeconomic position, gender, and social support, meaning that people with high socioeconomic position are more likely to use MHDS than people with low socioeconomic position, females are more likely to use MHDS than males, and people with high levels of social support are more likely to use MHDS than people with low levels of social support. MHDS usage thus seems to have a social gradient.

For the MHDS users, we do not know the details of their MHDS usage and in-person treatment because of the nature of the short survey. However, we do know that the most common tools are video consultations (59.7% of the users) and apps (45.6% of the users). Relatively few participants have been in online therapy (16.7% of the users) or used artificial intelligence (11.6% of the users), sensor technology (10.4% of the users), or virtual reality (3.7% of the users). Video consultations were most often suggested by a welfare professional, whereas apps were most often found by the users themselves. The next section looks more closely at the LCA for MHDS users.

## 8. Analyses of (Differentiated) Experiences and Attitudes Towards MHDS

### *8.1. LCA for MHDS Users*

Table 4 shows the IC for eight latent class models. The IC favor different models. As mentioned previously, the BIC is given superiority and a three-class model is chosen. In comparison to the other IC, the BIC prioritizes parsimony and reduces model complexity and the risk of overfitting (Weller et al., 2020). Indeed, the AIC and *a*BIC would induce too much model complexity, both suggesting an eight-class model. In this case, it seems fruitful to prioritize parsimony over complexity.

**Table 4.** IC and entropy for eight latent class models, MHDS users.

| N classes | BIC | AIC | *a*BIC | Entropy |
|---|---|---|---|---|
| 1 | 3152.81 | 3077.45 | 3095.67 | 1.00 |
| 2 | 2657.98 | 2503.09 | 2540.54 | 0.80 |
| 3 | 2549.43 | 2315.01 | 2371.69 | 0.78 |
| 4 | 2595.77 | 2281.80 | 2357.72 | 0.76 |
| 5 | 2629.57 | 2236.07 | 2331.22 | 0.77 |
| 6 | 2696.97 | 2223.93 | 2338.31 | 0.78 |
| 7 | 2750.05 | 2197.47 | 2331.09 | 0.79 |
| 8 | 2789.72 | 2157.60 | 2310.45 | 0.82 |

Note: Highlighted cells indicate the best model solution.

Figure 1 shows the average item response probabilities for each latent class and the latent class prevalences. The item response probabilities concern the likelihood of observing a particular response, for instance "agree or strongly agree," given class membership. In Figure 1, the item response probabilities are shown as average values across the items mentioned in Secition 6.2 for the MHDS users. Supplementary File 3 shows all the raw item response probabilities for both LCAs. The latent classes are characterized and named via the item response probabilities. For instance, the latent class "Self-help" is so named because members of this class are likely to agree with positive statements about MHDS. The latent class "Neither good nor bad" is named in this way because the item response probabilities show that members of this latent class are likely to neither agree nor disagree with the statements about MHDS, indicating a somewhat ambivalent position. A possible interpretation could be that these individuals do not think that MHDS have had a notable influence on their mental health. Item response probabilities for the latent class "Not useful" reveal that members of this latent class have a negative outlook on MHDS, being likely to disagree with positive statements about MHDS.

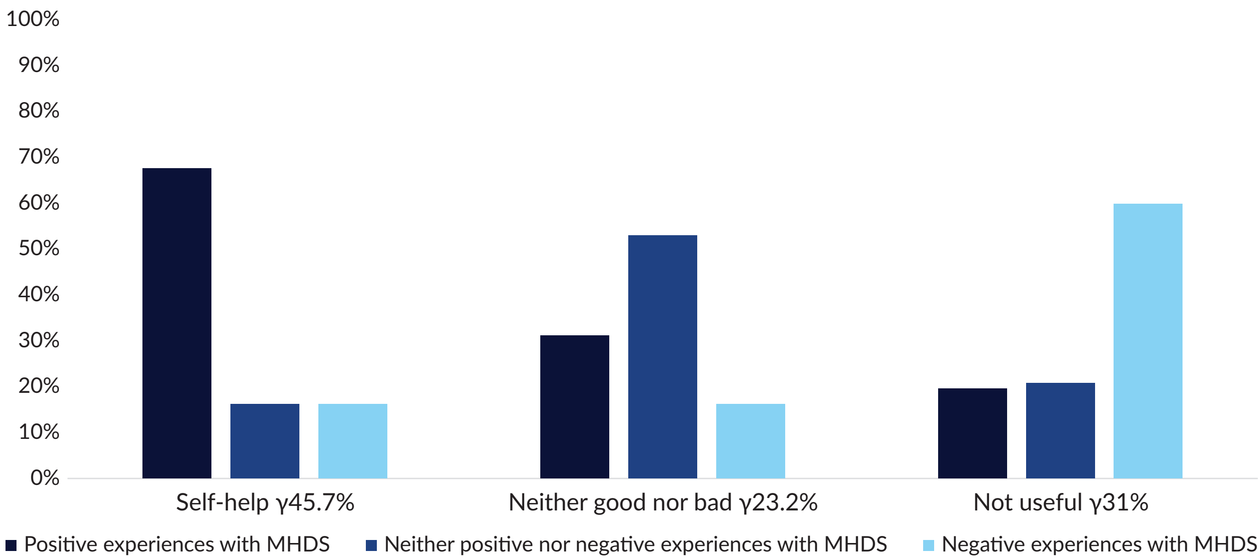


**Figure 1.** Average item response probabilities for each latent class and latent class prevalences ($\gamma$). Notes: $N = 486$; the response categories "Do not know" and "Prefer not to answer" are coded as missing values; 5 responses with missing values on all items were excluded from the analysis; recoded item categories: "Agree" and "Strongly agree" = Positive, "Neither agree nor disagree" = Neither positive nor negative, "Disagree" and "Strongly disagree" = Negative; two items were reverse-coded.

As the latent class prevalences in Figure 1 show, the positive “Self-help” class is the largest class in the population, covering 45.7%. However, the second-largest class is the critical “Not useful,” covering 31% of the population. Lastly, the ambivalent “Neither good nor bad” class is the smallest, covering 23.3%. We will next take a step further and examine whether the predictors are associated with the latent classes for MHDS users.

### 8.2. Regression Analysis for MHDS Users

Table 5 shows the results of the multinomial logistic regression analysis of the three latent classes and the predictors age, socioeconomic position, severity of mental illness, social support, geographical location, migrant status, and gender. The regression analysis is based on the sample of the LCA for MHDS users. However, the number of observations differs because participants with missing data on any of the predictors are excluded from the analysis. All continuous variables have been standardized. Among the latent classes, the “Not useful” class was the reference category.

**Table 5.** Multinomial logistic regression analysis for MHDS users with odds ratios for latent class membership.

| Predictor | Neither good nor bad | Self-help |
|---|---|---|
| Age | 1.07 | 1.42* |
| Socioeconomic position | 0.95 | 0.88 |
| Geographical location (ref. small city) | 0.90 | 1.00 |
| Gender (ref. male) | 0.97 | 1.05 |
| Social support | 0.90 | 1.34* |
| Migration status (ref. non-Danish) | 2.34 | 0.85 |
| Severity of mental illness (ref. non-severe) | 1.18 | 1.40 |

Notes: $N = 448$; Likelihood Ratio $\chi^2 = 25.71$*; log-likelihood = −454.87; * $p < 0.05$, ** $p < 0.001$.

The full model in Table 5 is significant ($p < 0.05$). Table 5 shows that there are no statistically significant differences between the “Neither good nor bad” latent class and the reference category “Not useful.” However, Table 5 reveals a positive association between age, social support, and membership of the “Self-help” latent class relative to the “Not useful” latent class. The fact that the other predictors are not significant could be related to low statistical power and be a limitation of the analysis. It could also be related to a selection effect, as demonstrated in the preliminary analysis of MHDS usage. The sample of MHDS users has substantially different characteristics than the non-users in terms of geographical location, gender, socioeconomic position, social support, and age. Figuratively speaking, this sample seems to consist of those who made it through the funnel.

Surprisingly, the association between age and the latent “Self-help” class is in the opposite direction than anticipated. Remembering that this sample is more likely to be comprised of younger participants compared to the non-users, it could be that those with a higher age in this sample have distinct qualities. It could be that they find MHDS more novel and impactful than those who are younger. Moreover, young individuals are more often exposed to digital tools, e.g., in educational settings or via social media, potentially making them less excited about MHDS. This would resonate with scholars who suggest that social media potentially inflicts young people with digital fatigue (Liu & He, 2021).

Further, Table 5 shows a positive association between social support and the “Self-help” latent class relative to the “Not useful” latent class. This lends a certain irony to the naming of the “Self-help” latent class. Members of this latent class are likely to feel that MHDS have, e.g., made it easier to manage their daily lives, and that they need less contact with their welfare professional. At the same time, they are likely to have higher levels of social support relative to the “Not useful” latent class, suggesting that they are not only more inclined towards self-help but also receive more help from others. Moreover, this challenges the individualistic connotation of self-help, underscoring the importance of having a network to draw on when managing mental illness.

### 8.3. LCA for MHDS Non-Users

This section follows the same LCA approach for the MHDS non-users. Table 6 shows the IC for eight latent class models. Again, the IC favor different models, and the BIC points towards a three-class solution, which is the model chosen. Importantly, entropy is the lowest for the three-class solutions, possibly imposing statistical uncertainty in the modal assignment used for the regression analysis. The entropy is not alarmingly low, but could serve as a limitation to the modal assignment.

**Table 6.** IC and entropy for eight latent class models, MHDS non-users.

| N classes | BIC | AIC | *a*BIC | Entropy |
|---|---|---|---|---|
| 1 | 534.20 | 506.16 | 515.14 | 1.00 |
| 2 | 363.48 | 302.74 | 322.20 | 0.75 |
| 3 | 285.15 | 191.71 | 221.64 | 0.67 |
| 4 | 302.00 | 175.85 | 216.26 | 0.78 |
| 5 | 305.36 | 146.51 | 197.40 | 0.80 |
| 6 | 339.39 | 147.84 | 209.20 | 0.84 |
| 7 | 372.10 | 147.84 | 219.67 | 0.87 |
| 8 | 378.89 | 121.93 | 204.23 | 0.90 |

Note: Highlighted cells indicate the best model solution.

Figure 2 shows the item response probabilities for responding “Yes” to the barrier items mentioned in Section 6.2 for each latent class and the latent class prevalences. The latent class “Lacking knowledge” receives this name because the item response probability for not knowing which tools are available is very high in this latent class. Conversely, the item response probabilities are low for the remaining items, indicating that these latent class members are not likely to face other barriers. Potentially, members of this latent class could have a positive outlook on MHDS if they knew which ones were available.

In contrast, members of the “Wanting in-person treatment” latent class seem to not use MHDS because they think they are less beneficial than meeting in-person with a welfare professional. Members of this class do not seem to have an aversion toward technology, given the low item response probabilities for the other items, but believe that digital therapy is of lower quality than in-person treatment. Again, this highlights the great importance attributed to welfare professionals.

Members of the “Multiple reasons for non-use” latent class seem to have medium-high item response probabilities on most of the items, suggesting that this class has multiple reasons for not using MHDS

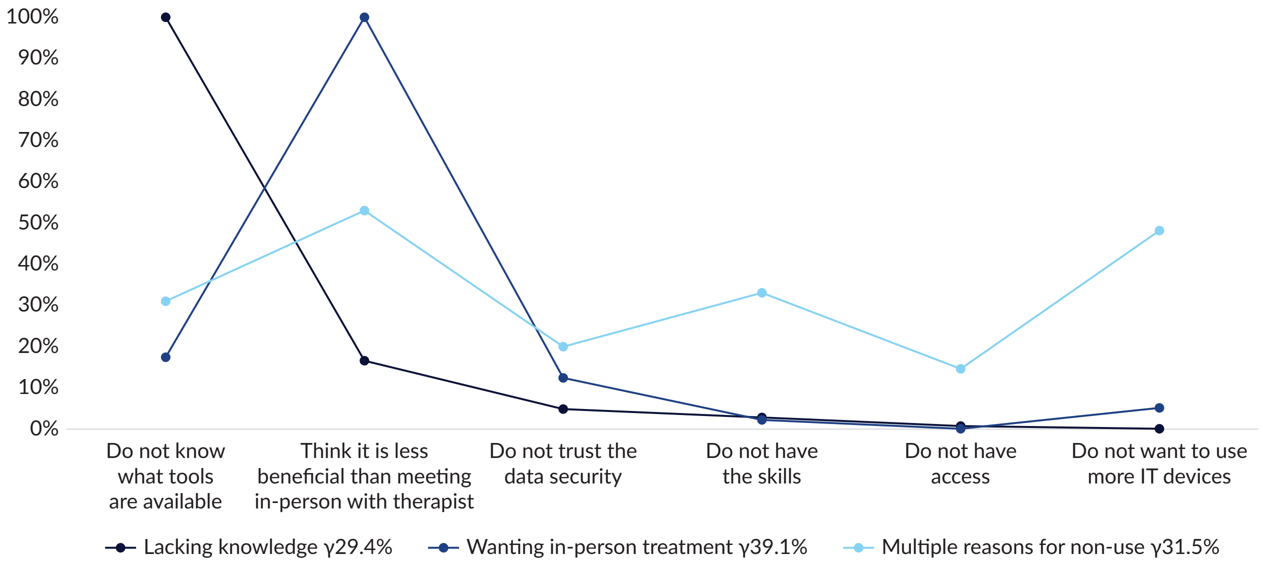


**Figure 2.** Plot of item response probabilities for each latent class and latent class prevalences (γ). Notes: $N = 790$; the response categories "I do not know" and "I prefer not to answer" are coded as missing values; 108 responses with missing values on all items were excluded before the analysis.

without any of the reasons being decisive. Moreover, many of the item response probabilities are homogenous for this class, making it difficult to articulate a clear characterization. This relates to the issue of latent class separation (Collins & Lanza, 2010), whereby it becomes difficult to separate the "Multiple reasons for non-use" latent class from the other latent classes. The most pronounced reasons are thinking that MHDS are less beneficial than meeting in-person with a welfare professional, not wanting to use more IT devices, and a lack of skills. Interestingly, none of the latent classes have high item response probabilities for a lack of access or trust in data security. However, members of the "Multiple reasons for non-use" latent class are more likely to face these barriers than members of the other latent classes. Thus, this latent class seems to be the most vulnerable in terms of MHDS.

Figure 2 shows that the three latent classes are somewhat equally distributed in the population. The hesitant latent class "Wanting in-person treatment" is the largest, covering 39.1%, while the critical latent class "Multiple reasons for non-use" covers 31.5%. In turn, 29.4% of the population belongs to the possibly open-minded latent class "Lacking knowledge."

### *8.4. Regression Analysis for MHDS Non-Users*

Table 7 shows the results of the multinomial regression analysis of the three latent classes and the predictors. As with the previous regression analysis, the number of observations differs from the LCA because responses with missing data on any of the predictor variables are excluded. The continuous variables were standardized and the "Multiple reasons for non-use" latent class serves as the reference category.

The full model in Table 7 is significant ($p < 0.001$). Table 7 shows a negative association between age and membership of the "Wanting in-person treatment" latent class and the "Lacking knowledge" latent class relative to the "Multiple reasons for non-use" latent class. Thus, older people are more likely to be members of the critical "Multiple reasons for non-use" latent class than the two other latent classes. At the same time,

**Table 7.** Multinomial logistic regression analysis for MHDS non-users with odds ratios for latent class membership.

| Predictor | Wanting in-person treatment | Lacking knowledge |
|---|---|---|
| Age | 0.69** | 0.64** |
| Socioeconomic position | 1.24* | 1.32* |
| Geographical location (ref. small city) | 1.42 | 1.15 |
| Gender (ref. male) | 0.84 | 0.81 |
| Social support | 1.03 | 1.05 |
| Migration status (ref. non-Danish) | 1.32 | 1.09 |
| Severity of mental illness (ref. non-severe) | 1.25 | 1.03 |

Notes: $N = 720$; Likelihood Ratio $\chi^2 = 39.62$**; log-likelihood = −748.12; * $p < 0.05$, ** $p < 0.001$.

Table 7 shows a positive association for socioeconomic position, indicating that individuals with higher socioeconomic position are more likely to be members of the “Wanting in-person treatment” latent class and the “Lacking knowledge” latent class relative to the “Multiple reasons for non-use” latent class.

The “Multiple reasons for non-use” latent class seems to be characterized by older age and lower socioeconomic position compared to the other latent classes. Importantly, this sample is already statistically associated with older age and low socioeconomic position compared to the MHDS users, as demonstrated in the preliminary analysis. The key features of this latent class are that its members face multiple barriers to using MHDS compared to the other latent classes and are more likely to face barriers related to skills and technology aversion compared to the other latent classes. This indicates that those who are the most critical towards MHDS among the non-users are also the most socially vulnerable—here, in the form of older age and lower socioeconomic position.

## 9. Discussion

The descriptive analysis of the usage of digital technology and the LCA for MHDS non-users indicates that, while not without importance, access does not seem to be a key barrier to using MHDS among psychiatric patients in Denmark. This is supported by Bonet et al. (2018), who find that psychiatric patients in Spain have similar access to technology compared to the rest of the Spanish population. In an American context, scholars similarly suggest that psychiatric patients have a comparable usage of technology to the rest of the population (Gay et al., 2016; Gitlow et al., 2017; Naslund et al., 2016).

There are other studies that suggest differently: Wong et al. (2020) find that people with schizophrenia in Australia have limited access to technology. However, the present study does not find associations between the severity of mental illness and the usage of MHDS or latent class membership. This could be related to sample differences; whereas Wong et al. (2020) focus on a small sample of individuals with a schizophrenia diagnosis, this study draws on a large sample where severe mental illness is understood more broadly as diagnoses with psychotic symptoms. Similar to Wong et al., Tobitt and Percival (2019) find that psychiatric patients in the UK have a substantially lower usage of technology than the rest of the UK population. The authors write that patients in the psychiatric facility under study often have long-term psychosis and “can be socially excluded” (Tobitt & Percival, 2019, p. 4). Thus, this sample may also vary substantially from that of the present study. As previously noted, severity of mental illness is a complicated matter, in which dimensions beyond the scope of this article such as duration of illness, need for in-patient treatment, and functional impairment could play a significant role in technology engagement.

Moreover, the importance of technology usage and access is disputed and could be sensitive to national contexts as well as sampling specificities. Still, this study supports the argument made by Torous et al. (2021) that time is a crucial factor and that technology access disparities are becoming less important. Instead, a lack of knowledge or motivation as well as the belief that MHDS are a poor replacement for in-person treatment could be key components of potential (self) exclusion.

As an empowerment initiative, MHDS pertain to broader modern sociological movements such as individualization and reflexivity (Giddens, 2009), do-it-yourself biography (Beck, 1993), self-technologies, and governmentality (Foucault, 1997). In different ways, these thinkers emphasize a turn away from traditional institutions towards the individual subject, which ought to be guided by self-optimization and self-determination. This entails critical reflexivity and the loss of irrevocable professional authority (Turner & Samson, 2007). Thus, scholars have illuminated how the empowerment and treatment inclusivity offered by digital solutions challenge the professional authority of welfare professionals (Denneson et al., 2017; Farnood et al., 2020; Fiske et al., 2020; Gabriels & Moerenhout, 2018). In line with the findings of Pilnick and Dingwall (2011), this study does not necessarily support this claim. Rather, participants seem to immensely value in-person meetings with welfare professionals.

The regression analysis for the MHDS users showed that members of the "Self-help" latent class are likely to have higher levels of social support relative to the "Not useful" latent class. The paradox of inclusion and assigning responsibility inherent in empowerment initiatives can also be related to social support. On the one hand, network involvement can be seen as a way of subverting authoritative hierarchies by enabling the network to understand and help the person in treatment. This could ensure sustainable welfare in the sense that one's network can provide long-term help and diminish dependency on welfare professionals. On the other hand, network involvement may be tied to the neoliberal focus on reducing welfare costs by diffusing responsibility to patients' networks. Seen from this point of view, the utilization of personal networks would inhibit socially sustainable welfare by leaving individuals without strong networks in a worse position than those who do have strong networks. This is not to say that network involvement is undesirable, nor that network involvement is borne out of neoliberalism. As with empowerment, the point is to flesh out a genuine dilemma, where inclusion and participation can go hand-in-hand with increased responsibility.

The regression analysis for the MHDS non-users showed that digital vulnerabilities are linked to social vulnerabilities. A critical interpretation could be that MHDS require patients to be resourceful in order to become (more) resourceful. This can be seen as an empowerment Matthew effect, exacerbating social inequalities if MHDS become the only treatment option. From a policy perspective, it is important to remember these structures. In the worst case, the implementation of MHDS could worsen the position of the most vulnerable groups of patients, who are not equipped for digital therapy. Additionally, given the overall importance attributed to welfare professionals, a socially sustainable digitalization of psychiatry would ensure that digital treatment does not supersede in-person treatment.

## 10. Conclusion

Paying attention to differentiating mechanisms underlying MHDS usage, this article presented a binary logistic regression showing that the predictors geographical location, gender, socioeconomic position, social support, and age are associated with MHDS usage. Second, the article presented two LCAs to characterize underlying groups among MHDS users and the non-users. The LCAs show that one size does not fit all. As shown with the latent class "Self-help," MHDS can be empowering for some patient groups. At the same time, others may feel left on their own as shown with the latent class "Not useful." Among non-users, MHDS can be excluding if they are experienced as the only accessible treatment option. This is particularly salient with members of the latent class "Multiple reasons for non-use." Finally, the article presented multinomial logistic regression analyses to examine the association between the predictors and the latent classes. These analyses reveal associations between age, social support, socioeconomic position, and the latent classes.

The article has used the concept of empowerment as an overall framework. Thus, the ambition of the article was to demonstrate how MHDS can be interlinked with both participation and increased responsibility. Importantly, empowerment is an ambiguous concept without a clear empirical foundation. This study has drawn on existing operationalizations of empowerment. However, no studies have constructed a validated measure for empowerment in relation to MHDS, and this could be an avenue for future research.

Furthermore, the findings do not seem to support the claim that MHDS diminish the importance of welfare professionals. Future research could examine the extent to which MHDS challenge, or perhaps reinforce, professional authority, as well as the ways in which social and digital inequalities may be mutually reinforced.

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### Conflict of Interests
The author declares no conflict of interests.

### Data Availability
The data are confidential and not publicly available. Please contact the author for further information.

## Supplementary Material

Supplementary material for this article is available online in the format provided by the author (unedited).

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