How Barriers and Facilitators Relate to Healthcare Professionals' Usage Patterns of Digital Mental Health Platforms: A Mixed-Methods Study

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Abstract

Digital mental health interventions (DMHIs) are rapidly evolving, leading to a lot of research to better understand and employ these interventions. One type of widely used digital mental health intervention is e-mental health platforms. Previous research has identified barriers and facilitators to platform adoption, but how these perceived factors relate to healthcare professionals' actual usage patterns is poorly understood. The aim of this mixed-methods study was to examine how mental healthcare professionals' perceived barriers and facilitators relate to their actual usage patterns on DMHI platforms used by mental health organizations throughout the Netherlands. Log data was collected from three different DMHI platforms and captured five activity types: client account creation, messaging, video calls, intervention assignment, and feedback. This data was analysed using principal component analyses and cluster analyses to identify usage patterns. Additionally, semi-structured interviews of 11 mental health professionals were analysed to gain more insight into platform usage, as well as perceived barriers and facilitators, providing context to quantitative findings. Principal component analyses and cluster analyses revealed that despite platform differences, two consistent user profiles emerged across all platforms, namely communication-focused users and administration-focused users. Furthermore, the platforms also revealed varying levels of usage intensity on usage patterns. The qualitative data identified barriers and facilitators that potentially play a role in the different usage patterns revealed from the log data. Commonly identified barriers included technical issues in communication. Facilitators included improved caseload management and client monitoring capabilities, which motivated continued platform use. The findings show that perceived barriers and facilitators can provide context for specific usage patterns. However, barriers and facilitators may also emerge from usage patterns themselves, as professionals who frequently use communication features encounter barriers as technical issues more often compared to individuals using more administrative functions. The findings demonstrate future research should explore the relationship between usage patterns and therapeutic outcomes to determine which approaches are most effective for mental health professionals and clients, as well as how certain barriers and facilitators develop over time. Limitations of the study include the small qualitative interview sample and the inability to measure the effectiveness of different usage patterns.

Keywords: Digital mental health interventions, usage patterns, log data, barriers, facilitators, mental health professionals

How Barriers and Facilitators Shape Healthcare Professionals' Usage Patterns with Digital Mental Health Platforms: A Mixed-Methods Study

The unprecedented number of people in need of mental healthcare presents a challenge to healthcare systems worldwide. In the Netherlands, 42% of people struggled with feelings of depression and/or anxiety in 2023 (Centraal Bureau voor de Statistiek, 2024). Healthcare shortages and global events such as COVID-19 have intensified the already growing need for mental healthcare, elevating the demand for alternative forms of mental healthcare services (Omary, 2020).

Digital mental health interventions (DMHIs) have emerged as a promising response to this crisis. These interventions offer advantages such as expanding access of mental healthcare to underserved populations, reducing costs, and alleviating the burden on mental healthcare professionals (Blease & Torous, 2023; Ramos & Chavira, 2019). As digital technologies evolve, solutions now range from self-help applications to hybrid platforms combining face-to-face therapy, and digital components with professional support (Pineda et al., 2023). Furthermore, research has shown that DMHI-based treatment can be just as effective as in-person therapy, especially cognitive behavioural therapy (CBT) for mood disorders (Balcombe & De Leo, 2022; Fernandez et al., 2021).

Despite the potential benefits, the successful adoption and use of DMHIs by mental healthcare professionals faces several challenges. These include organisational resistance to challenge, such as fear of the unknown and loss of control over established therapeutic practices (Bulling, 2022; Graham et al., 2020). Technology-related barriers encompass digital literacy concerns, privacy issues, lack of training, and apprehensions about technology's impact on the therapeutic relationship and the professional identity of a mental healthcare professional (Davies et al., 2020; Oudbier et al., 2024). Additionally, professionals raise concerns about ethical regulations and the perceived impersonality of online therapy as implementation challenges (Berardi et al., 2024). Despite these barriers, many organisations have already integrated DMHI platforms into practice.

To gain better insight into the usage and outcomes of DMHIs, log data from digital mental health platforms has been used to track clients' progress and understand client behaviour, such as motivation for online treatment and dropout patterns. (Turkington et al., 2018; Van Gemert-Pijnen et al., 2014). Additionally, perceived barriers and facilitators of DMHI usage by professionals have been identified through surveys and interviews. However, little attention has been paid to mental healthcare professionals' actual usage patterns through log data analysis, with most research focusing on client perspectives or professionals' attitudes toward DMHI usage instead. This leaves a gap in knowledge: we lack understanding of how professionals actually use these platforms and whether their perceived barriers relate to their real usage patterns. Understanding this relationship is particularly important in conceptualizing where we stand in the integration of technology in mental healthcare. Furthermore, understanding professional usage behaviour is essential for developing effective implementation strategies and improving platform design.

A mixed-methods approach is particularly suited to address this gap, as it allows for triangulation of objective usage behaviours with subjective experiences, to gain insight not only how mental healthcare professionals objectively use these platforms, but also why they might use the platform a certain way. Understanding this relationship can support in developing implementation strategies and improve platform design to encourage DMHI usage among mental healthcare professionals. This is important as DMHIs can increase access to mental healthcare, due to the improved accessibility of the therapist (Graham et al., 2020).

Given this gap, this study aims to provide a more comprehensive understanding of DMHI implementation in mental healthcare from professionals' perspectives, by combining objective usage data from three different e-mental health providers and subjective experiences from mental healthcare professionals.

Research questions:

1. How do mental healthcare professionals' perceived barriers and facilitators of Digital Mental Health Interventions relate to their actual usage patterns?

Sub-questions

1. Which barriers and facilitators do mental healthcare professionals experience with Digital Mental Health Intervention usage?
2. Which usage patterns can be identified through principal component analysis and cluster analysis?

Methods

Design

This convergent parallel mixed-methods study investigated how mental healthcare professionals' experiences with DMHIs relate to their actual usage patterns of digital mental health interventions. Quantitative log data from three DMHI platforms part of the eHealth Academy data sharing agreement was analysed to identify usage patterns across different organisations. Qualitative interviews with mental healthcare professionals regarding barriers and facilitators to DMHI usage, previously conducted at the Erasmus University Rotterdam, were analysed. The qualitative and quantitative data were collected and analysed separately, and then triangulated to understand how perceived experiences relate to objective usage behaviours.

Participants

Log data

Three datasets were supplied by three digital mental health platforms operating in the Netherlands, namely NiceDay, Therapieland and Minddistrict. From now on, these will be named platform A, B and C in a randomised order due to anonymity agreements made within the eHealth Academy. Log data was collected from mental health professionals in the Netherlands using one of these platforms in their practice. The datasets initially included much more data but were reduced to ensure a manageable and representative sample, which was ensured by using stratified probabilistic sampling to select the data included in the datasets for the current research. Each individual in the dataset represents any person working within organisations using these platforms, with no additional inclusion criteria besides platform usage. These individuals include psychologists, mental healthcare nurses, and other staff members such as secretaries who use the platform in their work.

The final sample consisted of 1166 participants, with 450 participants from platform A, 416 participants using platform B and 300 participants using platform C. The dataset was fully anonymized, assigning a unique ID code to not only each professional, but also to the organization they work for, ensuring no information can be identified.

Interviews

Semi-structured interviews conducted for a previous study with the same log data (Teng, 2024) were analysed. Interview participants included psychologists, nurse practitioners, GZ psychologists and psychotherapists with experience using NiceDay, TherapieLand or Minddistrict in practice. All participants were at least 18 years old and participation was voluntary. Recruitment occurred through email invitations sent via DMHI platform account managers. Participant demographics can be found in table 3. The first column of each variable refers to all participants, and the second column shows the demographics of just the medium and high interviewees. Based on described usage patterns, interviewees were categorized as low, medium, or high users. Only medium and high users were selected for analysis, as their usage patterns aligned with the high user group identified in the log data. High users were individuals who used the platform on a daily basis. Medium users were individuals that used at least one part of the e-health platform in the majority of their treatments. This resulted in seven interviewees.

Table 3

Demographics Interviewees

Characteristics	*Total*				*Med/high users*			
	n	*%*	*M*	*SD*	*n*	*%*	*M*	*SD*
Gender								
Male	2	18.2%			2	28.6%		
Female	9	81.8%			5	71.4%		
Type of healthcare professional								
Nurse	1	9.1%			1	14.3%		
Practitioner	6	54.5%			2	28.6%		
Psychologist	3	27.3%			3	42.8%		
Basic Psychologist	1	9.1%			1	14.3%		
Other								
Age			37.5	13.2			33.7	12.3
Mental Healthcare Experience in Years			8.5	9.6			8.5	10.6
DMHI Experience in Years			4.3	3.1			5.1	3.4

note: first column per category is the total demographics, second column per category are the interviewees used in this study

Materials

Log data

The data was collected for a period from January 3, 2022, until March 31st, 2024. The log data was presented in long format, with each row representing a single activity on the platform. Data collection automatically started as soon as professionals started using the DMHI platforms and registering activities. When a professional used the platform and an event was registered, a row was created in the data log, with one column that captured the organization ID (code referring to the organization the professional works for), a column for the personalized professional ID (unique identifier for the professional), a column with the professional cohort (referring to when the professional account was created), a column with the date and time the activity occurred, and a column stating the type of activity performed.

For every platform, the same five different activities were registered, with each occurrence of each activity creating a separate entry in the dataset: 1. Client account created, referring to when the therapist created a client account on the platform; 2. Message sent, referring to text-based interaction between the therapist and the client; 3. Video call started, referring to when a video call was initiated for therapy sessions; 4. Intervention added, referring to a therapist assigning an intervention or module from the e-mental health platform to a client; 5. Feedback sent, referring to when a therapist sends feedback after the client completes one of the in-site exercises.

Interviews

Semi-structured interviews were conducted using an established set of questions covering seven main topics: introduction, usage of DMHIs, digital proficiency, factors contributing to sustained usage, challenges, therapeutic alliance, and a closing question asking if there was anything the interviewees wanted to share. The interviews were conducted digitally using Microsoft Teams and audio recording equipment was used to record the interviews.

Procedure

Interviews

Prior to the interview, all participants were asked to sign a written consent form outlining the purpose of the study, procedure, potential risks and benefits, a confidentiality statement, and withdrawal rights. All identities were anonymised. While following the interview structure, questions could be modified based on participant responses. All interviews were recorded and transcribed verbatim.

Data Analysis

Log data

R Studio (Version 2024) was used for data analysis of the log data. The datasets from each platform was compiled into one dataset, capturing five activity types across all platforms. Activity counts per platform can be found in table 1. The data was originally presented in a long format dataset, so to improve comprehensiveness of the data it was transformed into a dataset where each row presented a single user, and each column the frequency of a specific event. Then, descriptive analysis was done on this dataset.

Table 1

Number of Events by Every Platform

	Platform A	Platform B	Platform C	Total
Client account created	22797	9803	3044	35644
Intervention added	21500	22513	10144	54157
Message sent	130557	1925	14009	146491
Video call started	54339	7270	7768	69377
Feedback sent	10979	65633	1856	78468
Total	240172	107144	36821	384137

Due to the different nature of each platform, the data analysis including the descriptive analysis has been done separately for each platform, as well as together. While the same five activity types were captured across all platforms, each platform has different features and functions. Separate analyses are necessary to account for these platform-specific differences and its potential effect on usage patterns.

The mean, median and mode of the various events presented that due to the size and nature of the dataset, a large number of individuals would not be as relevant in the data analysis for this paper. Every person that used the DMHI platforms in the timeframe would be added to the database, resulting in many individuals with one singular entry. Furthermore, there are many individuals with no sustained engagement (very low average per day). While documenting low engagement is relevant for understanding successful implementation, it provides limited insight into the characteristics of successful platform adoption or meaningful usage patterns that relate to usage barriers and facilitators. To address this issue and better understand actual usage patterns, the decision was made to categorize users based on their level of platform engagement. Three categories were created: high users (>66th percentile), medium users (>33rd percentile and <66th percentile) and low users (<33rd percentile).

When examining activity levels of the different categories, low and medium users had a max daily activity average of <10. To keep the focus on actual usage patterns, the focus from here on out will be on the 'high' category, unless otherwise mentioned. The proportion of high users varied by platform, with B having the greatest percentage of high users (table 2).

Table 2

Percentages of User Groups by Platform

	A	B	C
Low users	36.22	19.23	48.67
Medium users	30.67	36.54	30
High users	33.11	44.23	21.33

An extreme outlier was identified in platform A. With 17,258 total actions on the platform, this user has 48% more platform interactions than the next highest user on this platform. This outlier was removed due to this research paper relying on patterns and averages.

To identify underlying patterns in the usage data, a principal component analysis (PCA) was conducted on the log data of each separate platform. PCA is a statistical technique that reduces complex datasets by identifying the most important underlying patterns and combining related variables into meaningful components, making it easier to understand what drives user behaviour on DMHI platforms. The variables used for the PCA include organisation id, client account created, videocall started, message sent, intervention added, feedback sent, total actions, days between first and last action and average action per day. A more elaborate explanation of the data used can be found in appendix A. Components explaining 80% of cumulative variance were retained, resulting in three components for platform A, four for platform B, and five for platform C. Communalities tables were created to assess how well each variable was represented within the retained components. The higher the value, the better the variable is represented in this principal component.

Based on the principal components, a cluster analysis was conducted to get more insight into the user patterns within these platforms. K-means clustering was selected as the best method to apply to these datasets due to the way the data is structured after the PCA. To determine the optimal number of clusters, the silhouette method, elbow method and NbClust, a function in Rstudio, was applied to each dataset separately. Cluster validity was assessed using the average silhouette width, within-cluster sum of squares and between-cluster sum of squares.

Interviews

Interview transcripts were analysed through systematic reading and summarisation. For each interview, information was extracted and summarised using the six predetermined categories: 1. DMHI platform used, 2. Type of mental health professional, 3. Internet proficiency (if mentioned), 4. Usage pattern (frequency, which features, face-to-face/blended/completely online), 5. Facilitators for the professional, and 6. Barriers for the professional. As the research concerns the usage patterns of the professionals, potential facilitators and barriers regarding clients (e.g. clients do not always know how to log in/clients are not motivated to do homework) were excluded. Barrier and facilitator categories emerged inductively during analysis. As each barrier or facilitator was identified, it was either assigned to an existing category found in earlier interviews or used to create a new category as needed (e.g. connectivity issues and video call issues were grouped as ‘technical issues’).

Triangulation

Following separate quantitative and qualitative analyses, triangulation was conducted to examine how perceived barriers and facilitators relate to actual usage patterns. Usage patterns identified through cluster analysis were categorized by their predominant features (e.g. communication-focused vs. administrative-focused usage). Barriers and facilitators extracted from interview summaries were organised into the categories that emerged during interview analysis. These findings were then systematically compared to identify similarities and differences between professionals’ reported experiences and their objective usage behaviours.

Results

Which usage patterns can be identified through principal component analysis and cluster analysis?

Principal component analyses

In total, 384137 actions were taken on all different platforms between January 3, 2022, and March 31st, 2024. Of these actions, 62.5% were taken within platform A, 27.9% by platform B and 9.6% by platform C. Users of platform A had an average of 534 actions, users of platform B took averagely 258 actions and platform C users had an average of 122 actions. Of the 384137 actions, 356,985 were taken by those considered high users. This is 93% of all actions taken. Of all the actions, 'message sent' was taken the most often for both platform A and C, but this was the action done least frequently by users on platform B. Users on platform B used the 'feedback sent' option the most frequently, whereas this was the action taken the least for users on platform A and C.

Platform A

Principal component analysis

To be concise, results of all the staps of the analyses will only be presented for platform A. For platform B and C, only the main outcomes will be presented. Other results are presented in appendix C. Principal component analysis of platform A high users identified nine components, of which three explain 85.3% of variance. Variance explained per principal component can be found in figure 1. Component loadings indicate the contribution of each variable to the component. PC1 had strong loadings on total actions, average actions per day, interventions added, client accounts created, and messages sent, suggesting it represents user engagement intensity. PC2 showed positive loadings on video call started, and message sent, with negative loadings on interventions added and feedback sent, representing the communication preferences of the individuals. PC3 had high loadings on days between first and last action, with a negative loading on average actions per day, which suggests this component represents temporal usage patterns. Specific loadings per component exceeding .3 can be found in table 4.

Figure 1

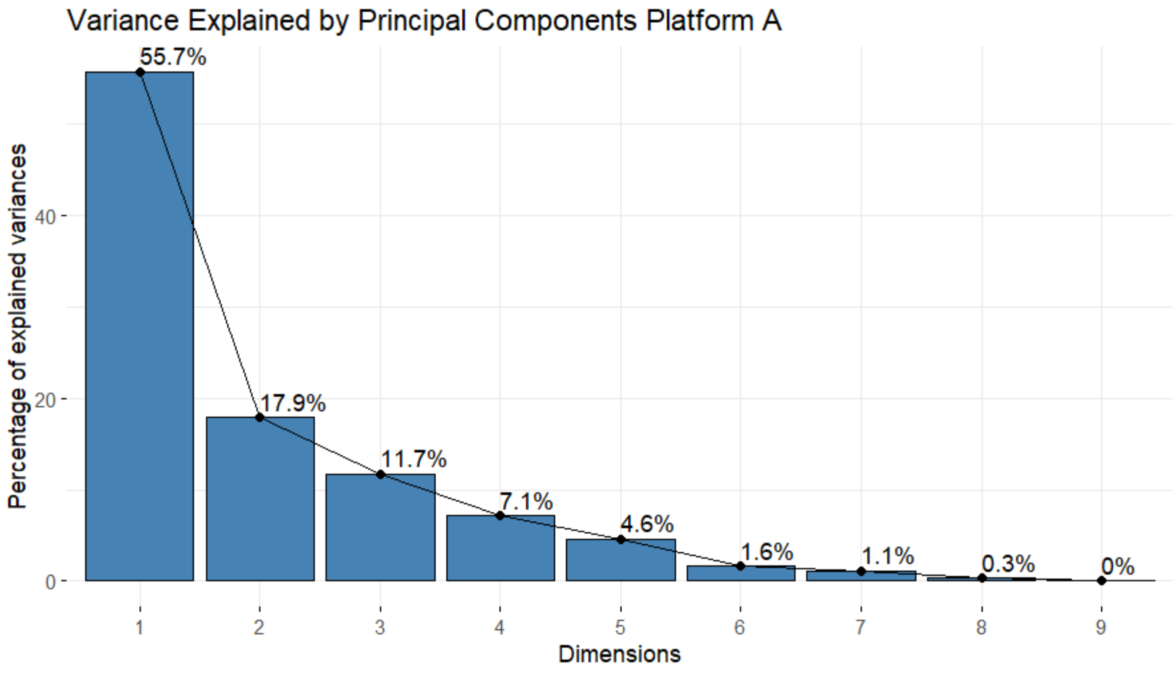


Table 4

Principal component loadings platform A

	PC1	PC2	PC3
Organization		.	
Feedback sent	.31	-55	
Message sent	.34	.42	
Videocall started		.5	
Intervention added	.39	-.31	
Client account created	.37		
Total actions	.43		
Days between first and last action			.95
Average number of actions per day	.41		

Note. Values <0.3 omitted.

The communalities show how well represented the different variables are in the three principal components that were retained. Communalities ranged from .15 to .9 (Table 5). Days between first and last action showed the highest communality (.9), while feedback sent and videocall started show moderate communalities (.4 and .32 respectively). The remaining variables showed lower communalities, ranging from .15 to .29.

Table 5

Communalities per variable in descending order

Variable	Communality
Days between first and last action	.9
Feedback sent	.4
Videocall started	.32
Message sent	.29
Intervention added	.25
Average number of actions per day	.21
Client account created	.20
Total actions	.19
Organization	.15

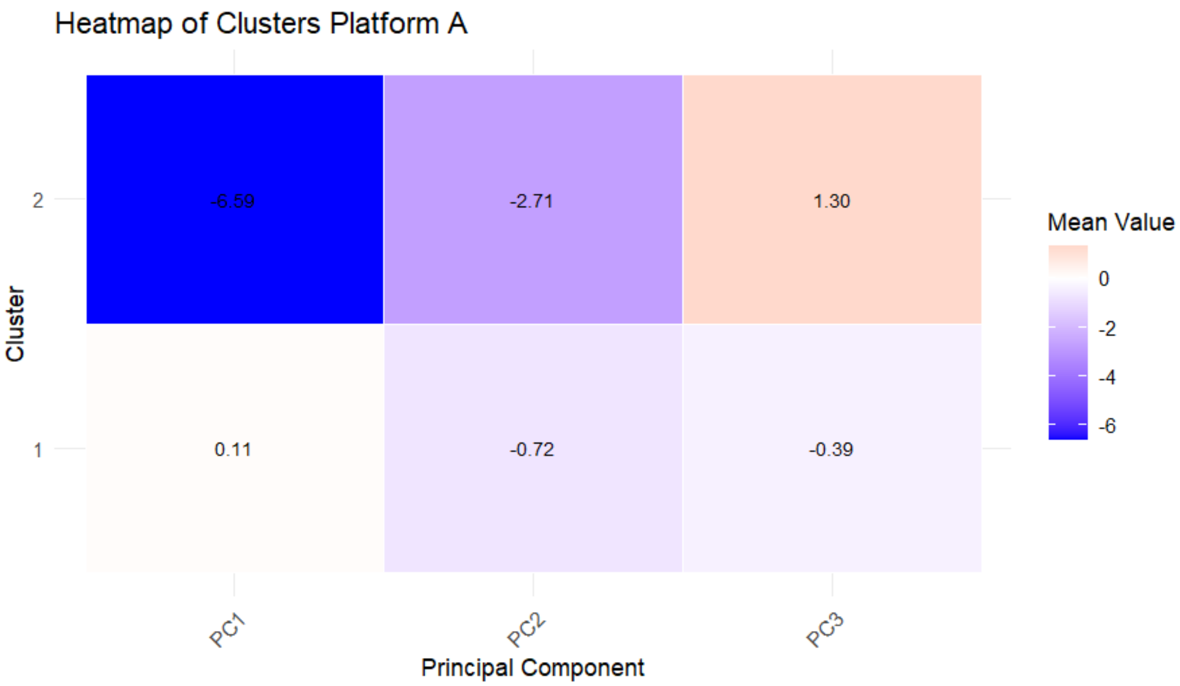
Cluster analysis

K-means clustering was done based on the principal components. Using the silhouette method, 2 clusters were identified as the optimal amount for analysis. Silhouette width was .78, and values above 0.7 suggest well-separated clusters. The elbow method and NbClust supported k=2 clusters. The silhouette graph and the elbow graph can be found in appendix B. The within-cluster sum of squares and between-cluster sum of squares were calculated and together resulted in a variance explained of 66%, suggesting good cluster separation.

The visualisation of the clusters across the different principal component dimensions reveals distinct behaviour profiles among users of platform A, separated into two clusters. Cluster 1 comprised 89% of users (n=131). And cluster 2 comprised 11% of users (n=17). When looking at the heatmap, it shows that cluster 1 scores positively on PC1, and negatively on PC2 and PC3. This indicates that this cluster is generally relatively active on the platform, with a slight preference for communicative actions over administrative actions and they generally did not use the platform for a long period of time. Furthermore, cluster 2 scored negatively on PC1 and PC2, and positively on PC3, indicating this cluster is not active on the platform, preferring communication activities when they do, and they did use the platform over a longer span of time. (figure 6).

Figure 6

Heatmap platform A



Platform B

PCA analysis revealed four principal components for platform B, representing usage intensity, administration versus communication preferences, organisational usage patterns, and communication method preferences. Three clusters were identified, a small cluster of varied-activity administrative users, a large cluster entailing 87% of all users of highly active administrative-focused users operating within specific organisation structures, and a cluster preferring administrative tasks with intermittent engagement. Complete results including component loadings and cluster visualisations can be found in appendix C.

Platform C

The PCA for platform C resulted in five principal components, indicating the higher user diversity among all platforms, with principal components representing overall activity, management preferences, interactions patterns, engagement duration, and synchronous versus asynchronous communication preferences. Four clusters emerged from the analysis. The first is a low-activity administrative group preferring asynchronous communication, a moderately active group with balanced preferences favouring synchronous communication, a small cluster of low-activity communication-focused users with synchronous activity preferences and the largest cluster entailing over 70% of all users. This cluster is highly active, long-term users with a preference for asynchronous communication. Detailed component loadings, communalities and visualisations can be found in appendix C.

Which barriers and facilitators do mental healthcare professionals experience with Digital Mental Health Intervention usage?

Content analysis of seven interviews revealed information across six predetermined categories. The first three categories (platform used, platform usage and type of mental health professional) were extracted from the text and will be summarised here. Furthermore, barriers and facilitators were extracted and then categorised, based on categories that emerged during the analysis. These themes can be found per interviewee in appendix D. Barriers and facilitators mentioned by at least two participants are discussed below, with frequencies in table 10 indicating common experiences across professionals.

Table 10

Frequency table barriers and facilitators

Theme	n
Facilitators	
Workflow enhancement	6
Improved client monitoring	5
Availability of tools	4
Barriers	
Technical problems	5
System integration issues	3
Limited availability of modules	2

Note. n = 7 interviewees

Two types of users emerged from the analysis. High users (n=3) who integrate platforms into daily practice, and medium users (n=4) who use the platform in the majority of their treatments. Interviewee 1 is categorised a high user: “I do use it every day throughout the whole day, and it is kind of the central platform for the treatment”, whereas interviewee 2 talks about platform as support, more in line with medium users: “I use approximately one module per client. It is support for the treatments”.

Workflow improvement was the most frequently mentioned facilitator (n=6), specifically enhanced client monitoring and session preparation. Interviewee 4 explained “I see a lot of value in being able to monitor your clients, so knowing how they are doing. Both on an individual level or caseload level, I can quickly see how someone is doing, but it also helps me prepare my sessions. So I know what they experienced this week. I know what they struggled with this week. I know what they practiced. It really helps me prepare my session.”. Two interviewees mentioned using the platform specifically to align with clients’ needs. Interviewee 7 mentioned: “one of the best things about e-health is that you can specifically tailor every module to the client”, and interviewee 1 said “I'll share specific articles or psychoeducation based on their complaints. So that's how I personalize the treatment. Most of the time and the frequency and the intensity of the online treatment, I will also manage based on the clients’ needs.”

The barrier mentioned most frequently is technical problems, ranging from issues with setting up the platform to connection issues during sessions (n=5). More specifically was mentioned a few times that occasionally, sessions need to end because of the lack of internet or other technical issues. This was given back from clients to interviewee 5: “Clients will say ‘I do not think this is a nice way of talking, because of the internet connection”. Besides, another often mentioned barrier is the lack of integration with other administrative systems required to be used in different organisations, such as systems required to report sessions in (n=3). This can cause extra work (e.g. reporting twice), leading to platform disuse. Interviewee 3 mentioned “Integration with other systems is an obstacle, meaning that you have to do double work sometimes”, which was supported by interviewee 4 “A barrier is that the administrative part is not inside the product and is being done in a separate system”.

Triangulation

To answer the research questions posed at the beginning of this paper, it is important to look at the connections between the quantitative and the qualitative results found in the research. The integration of the quantitative log data and qualitative interview data reveals various patterns that strengthen the understanding of DMHI platform usage. An overview of this integration can be found in table 11.

Table 11

Triangulation

Quantitative	Qualitative	Triangulation
Usage intensity varies between platforms	DMHI fulfils a different role for different professionals	Convergent
Active users of platform A and C prefer communication methods	Professionals on these platforms use mainly communication methods	Convergent
Some platforms show temporal patterns	Interviews reveal three distinct temporal usage patterns: consistent, alternating and contextual	Convergent

Cluster analyses showed that a majority of the high users prefer communication methods over administrative methods on the platform. Cluster 1 of platform A, which entails 89% of high users, as well as platform C's clusters 3 and 4 (73.4% of high users) have a strong preference for communication methods, specifically with high usage on messaging and video calls. Platform B was an exception, with most users leaning toward administrative tasks. This was supported by different interviews, with interviewees from platform A emphasizing communication, with interviewee 1 mentioning "What I mostly use is video calling and chatting to clients", and interviewee 4 "I am mainly focused on giving online treatment, which means video calling and chatting". The interviewees from platform B however (2, 5, 6) described to use the platform as more of a supportive role in therapy. This convergence between the log data and interview reports indicates alignment between reported experiences and actual usage behaviours.

Another variable is activity level and usage intensity, which varied significantly across platforms and users. Quantitative data showed platform A averaged 534 actions per professional, whereas platform C had an average of 122 actions per professional. Interview data gave some insight into this variation. Some professionals exclusively use the platforms for all parts of therapy, such as interviewee 3: "Once every two weeks I have an appointment on video conferencing, and the other week I give written feedback". Other professionals use the platform as support for face-to-face therapy, for example interviewee 2: "I use approximately one module per client…it is a really good support for the treatment". This demonstrates how the same platform can serve different roles, accounting for the range in usage intensity observed in the log data even if both interviewees are considered high users.

PC3 for platform A showed temporal patterns, suggesting that cluster 2 had less frequent usage than cluster 1, but this cluster used the platform more sustained and longer-term than cluster 1. The interviews show individuals with consistent usage “Each week I have an appointment with my client and they make a module every week”, as mentioned by interviewee 7, alternating patterns “One week I have an appointment on video calling and the other week I give written feedback”, mentioned by Interviewee 3 and lastly contextual usage by interviewee 5 “Most of the time I give the programs as assignments to do at home, or sometimes we do it during the therapy sessions”. The interviews give some insight into how these temporal patterns come to be.

The qualitative insights lining up with the quantitative data allows for some connection between the usage described by the interviews and the patterns observed in the log data.

Quantitative data showed platform A averaged 534 actions per professional, whereas platform C had an average of 122 actions per professional. Interview data revealed that some professionals exclusively use the platforms for all parts of therapy, such as interviewee 3: “Once every two weeks I have an appointment on video conferencing, and the other week I give written feedback”. Other professionals use the platform as support for face-to-face therapy, for example interviewee 2: “I use approximately one module per client…it is a really good support for the treatment”. This demonstrates how the same platform can serve different roles, accounting for the range in usage intensity observed in the log data even if both interviewees are considered high users.

Discussion

This study aimed to investigate how perceived barriers and facilitators in the usage of digital mental health interventions (DMHIs) relate to the actual usage behaviour of mental healthcare professionals using a mixed-methods approach. The results of the quantitative and qualitative analyses showed associations between the actual usage behaviour patterns of mental healthcare professionals and barriers and facilitators they experience, though through the study, the direction of causality was questioned. The findings revealed that mental healthcare professionals experience diverse barriers and facilitators when using DMHIs, with facilitators primarily focused on improving work quality and treatment ease, while barriers centred on system integration issues and technical difficulties. Principal component analyses and cluster analyses identified distinct usage patterns across platforms, constantly differentiating between communication-focused and administrative-focused activity patterns, as well as varying usage intensities. The relationship between perceived barriers and facilitators, and actual usage patterns proved complex, and potentially bidirectional. While some barriers and facilitators may precede and potentially influence platform adoption, others emerge during use and may be consequences rather than causes of specific usage behaviours, challenging assumptions about the direction of causality in DMHI adoption.

Mental healthcare professionals reported varied facilitators that primarily revolved around improvement of workflow and quality, and enhanced treatment delivery. Professionals frequently mentioned improved insight into their clients well-being and a better overview of their caseload as a key facilitator. Research by King (2009) has shown that the active monitoring of caseload is associated with lower work related stress levels. This level of monitoring is easier to achieve through DMHIs. Additionally, access to evidence-based resources was identified as a treatment facilitator, providing valuable treatment support in the form of psychoeducation and homework assignments. These modules have also been proven to be effective in educating individuals and increasing mental health understanding (Ardiani & Mardiyah, 2023). Additionally, they have also proven effective for treatment in depression (Batterham et al., 2015). However, professionals also encountered barriers, most notably the lack of integration with other systems, which can decrease productivity and create redundant work, while mental healthcare professionals are already struggling with long waitlists and work pressure (Adrichem & Bijkerk, 2024). Furthermore, technical problems, particularly unstable connections in therapy through video calling were frequently mentioned as barriers that could negatively affect effectiveness of online therapy. This is problematic as according to Bulling (2022), online therapy can be as effective as face-to-face therapy, but only if properly implemented, which is in some cases inhibited by this factor. These findings suggest that while DMHIs offer benefits for treatment enhancement for the mental healthcare professional, some structural and technical challenges remain obstacles to implementation.

The quantitative analysis revealed consistent patterns in how mental health professionals engage with DMHI platforms. Firstly, it was revealed that high users (the top 33%) accounted for 93% of all platform actions within the log data, indicating significant variation in DMHI integration into treatment. Furthermore, principal component analyses identifying a clear distinction between communication-focused activities (video calls, messaging) and administrative-focused tasks (adding interventions, creating client accounts) across all platforms. This distinction suggests that professionals approach platforms with different therapeutic intentions and workflow preferences, which was supported by interview findings. This could be related to different attitudes practitioners have towards DMHIs in mental healthcare, as practitioners without experience are more cautious in using DMHIs in their treatments (Mittmann et al., 2024), even though the interviews revealed that some individuals exclusively use the platforms for their treatment. Research by Sander et al. (2021) also suggests that attitudes toward blended therapy are generally more positive than exclusively online, which could explain these different usage intensity levels. The various platforms also had differences in usage patterns between them. Platform A had the highest average actions, with also the most similarities in their users. Users on platform B and C were not only less consistently active, there was also a greater variation in user profiles. This suggests that not only the way the users engage with the platforms account for differences, but the different platforms also influence the way DMHIs are integrated in therapeutic practice.

The integration of qualitative and quantitative findings revealed a complex relationship between perceived barriers and facilitators, and usage patterns. Log data reveals that communication-focused usage patterns often revealed higher usage intensity, suggesting that communication features are more frequently used by those providing complete online therapy compared to those using blended approaches. This aligns with research indicating that healthcare providers prioritize interventions, or features that meet their needs (Damschroder et al., 2009). Notably, the analysis revealed that instead of barriers and facilitators preceding adoption, many barriers and facilitators might emerge during use. For example, professionals exclusively giving online therapy reported technical issues as barriers, even though they will continue to use video calling as form of therapy due to necessity. Similarly, professionals using platforms for administrative tasks encountered integration barriers not because these barriers shaped their usage preferences, but their administrative focus made them more likely to experience these specific challenges. This is in line with the technology acceptance model (TAM), suggesting that perceived usefulness in practice influences the usage rate of new technologies (Venkatesh & Davis, 2000). This finding suggests that perceived barriers may often be consequences rather than determinants of usage behaviour, with user behaviour potentially influencing which barriers are perceived and experienced. Furthermore, platform-specific variations in barriers and facilitators, such as limited questionnaire availability indicate that user experiences depend on platform selection, while organizational influences create additional variation in both usage patterns and perceived barriers, as some users may not encounter certain barriers due to organizational methodology in using DMHI platforms.

Conclusion

Strengths and limitations

There are several strengths to be highlighted in this study. The convergent parallel mixed-methods approach combining log data analysis with qualitative interviews provided comprehensive understanding of DMHI usage that neither method alone could achieve, with quantitative patterns explaining usage behaviours and qualitative data revealing underlying motivations. With just the log data, variables like different usage intentions would have been much more difficult to understand and take into account when analysing the data. Furthermore, without the log data, it would have been much harder to see how certain barriers and facilitators actually influence usage. The large sample size from three different platforms and multiple organisations enhanced the generalisability of findings. The extensive period of time in which data was collected captured sustained usage patterns and changes in those patterns over time. This provided insight into true patterns and established usage practices, instead of potentially skewed usage patterns due to novelty of the platforms. Finally, the convergence between quantitative usage patterns and qualitative interview descriptions strengthened confidence in the validity of both data sources.

However, several limitations should be considered when interpreting these findings. The sampling strategy for interviews likely introduced selection bias, as individuals willing to discuss their DMHI usage are more likely to be passionate about it, resulting in predominantly medium and high users (7 out of 11 interviews), potentially overlooking barriers experienced by low users who may avoid platform engagement entirely. The log data, while extensive, could not capture interaction quality, content, or effectiveness. Furthermore, it could also not reveal contextual factors, such as whether professionals used DMHIs for fully online therapy, or if they used a blended method, as well as countless other reasons usage might be influenced. This would allow for a better separation of users, understanding more clearly how some patterns emerge. Due to the high number of users that only had one action logged on the platform, the decision was made to focus on the high users of the platform, potentially missing barriers and facilitators faced by low and medium users, whose challenges may differ. Lastly, even though the same data was extracted from the usage logs of the platforms, each platform is different. As a result, the same professional might face different types of barriers in their usage depending on the platform they use, showing that barriers are not only determined by the users' or treatment approach, but also by the specific design and features of the individual platforms.

Future research

Future research should explore the relationship between usage patterns and therapeutic outcomes to determine gain insight into the effectivity of various usage patterns. This can inform the platforms and organizations about how the implementation can be improved, and improve client care. Additionally, conducting longitudinal studies tracking how usage patterns evolve as professionals gain experience would be valuable for understanding implementation trajectories, and provide a clearer picture on how implementation can be effective. Furthermore, taking the point at which facilitators and barriers are noticed, and how this affects usage would improve insight into which barriers might actually deter usage, for example. Finally, gaining more insight into how professionals use the platform (fully online, blended, modules only) could also give a better understanding of usage patterns which can inform the platforms and organizations about better implementation.

Conclusion

This mixed-methods study investigated how mental health professionals' perceived barriers and facilitators relate to their actual usage patterns of digital mental health interventions, revealing that the relationship between experiences and behaviour using DMHIs is more complex that initially expected. The analysis of log data from three DMHI platforms alongside professional interviews identified distinct patterns that showed alignment with professionals' reported experiences while also revealing unexpected complexities. A key finding was that barriers did not necessarily influence usage for the interviewees, suggesting that barriers and facilitators do not have to affect adoption or usage intensity. Instead, some barriers and facilitators may emerge as a consequence of usage patterns, rather than determining them, and platform or organizational difference can influence whether certain barriers even exist for professionals. While the mixed-methods approach provided valuable insight and the large sample size improved generalisability, several limitations should be noted, including the tendency for interview participants to be higher users, and the inability to capture the quality of platform interactions. Besides, important contextual factors were not available in analysing the log data. The results indicate that successful DMHI implementation requires understanding of how barriers and facilitators emerge and change over time during platform use, rather than viewing them as fixed factors that predict usage. Future research should examine how usage patterns from mental health professionals relate to therapy outcomes for clients, investigate how barriers and facilitators evolve as professionals become more experienced with platforms, and explore how specific platform features and organisational contexts interact with individual professional preferences to shape how digital mental health tools are integrated into clinical practice.

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During the preparation of this work the author used Microsoft editor for spelling and grammar checks. The author also used Scribbr to create APA references. After using this tool, the author reviewed and edited the content as needed and takes full responsibility for the content of the work.

Appendix A

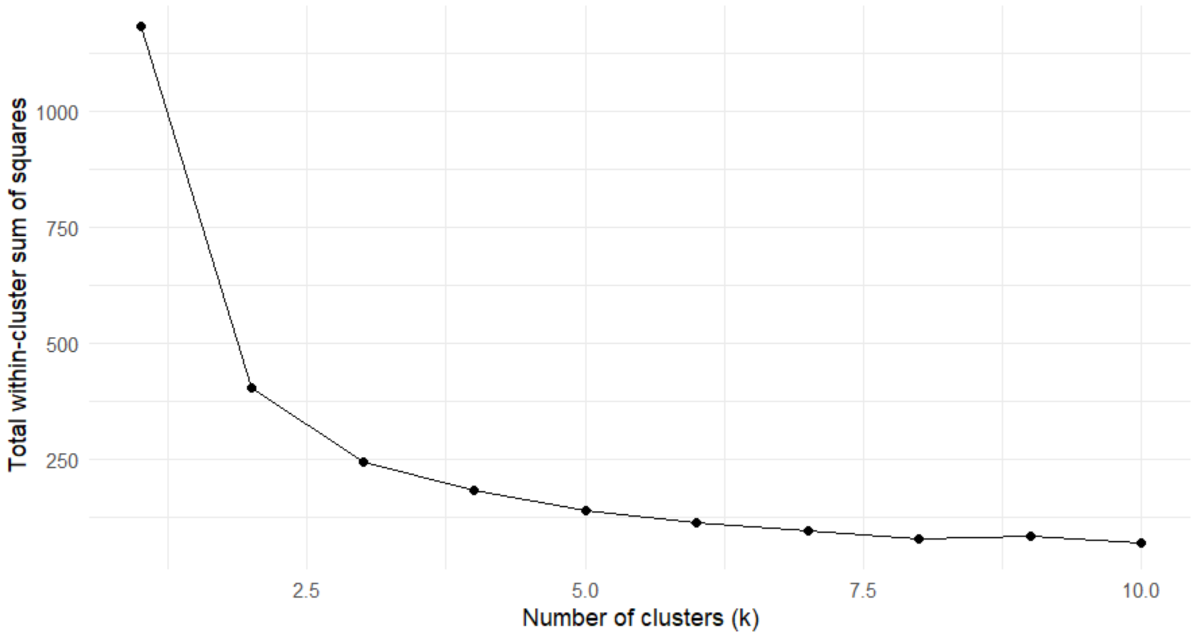
Table A1

Variables used in principal component analyses

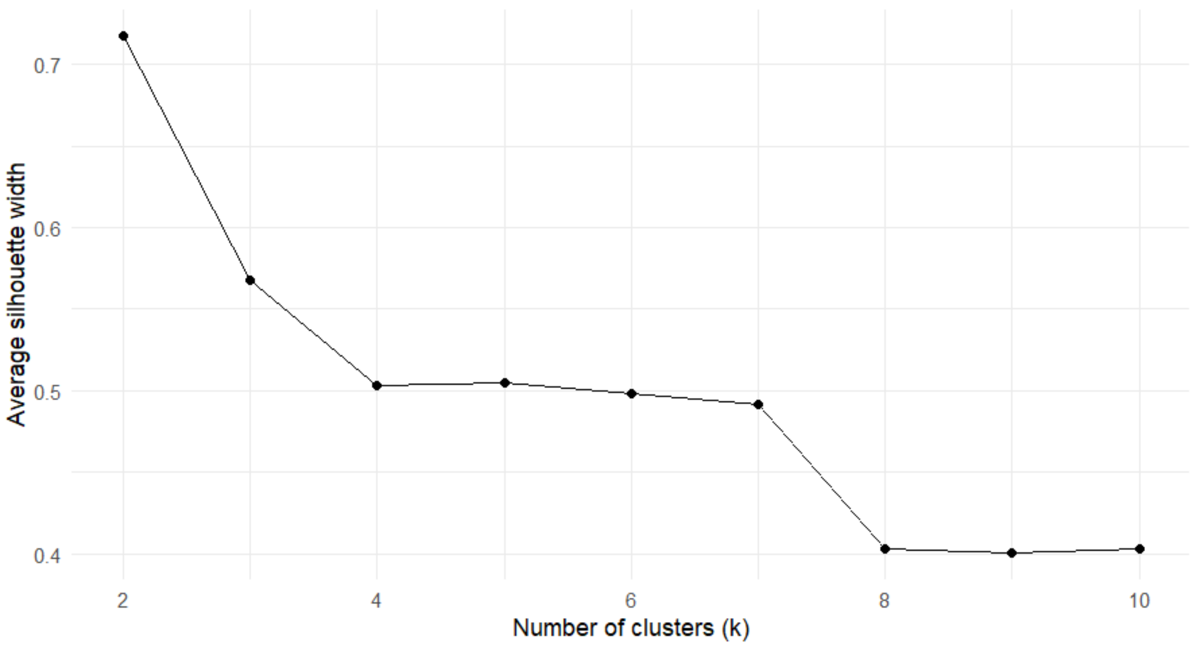
Variable	Explanation
Organization ID	Unique anonymized ID for different organizations assigned to individuals that work at each organization.
Feedback sent	When a professional gives feedback on an online e-health module (intervention) a client did.
Message sent	When the professional sends a message to a client.
Videocall started	When the professional joins a videocall with a client.
Intervention added	When the professional assigns an online e-health module to the client
Client account created	When the professional creates a new account for a client
Total actions	The total actions the professional has done on the platform since first use
Days between first and last action	The amount of time across which the professional has used the platform
Average number of actions per day	The average number of actions a professional did per day while using the platform

Appendix B

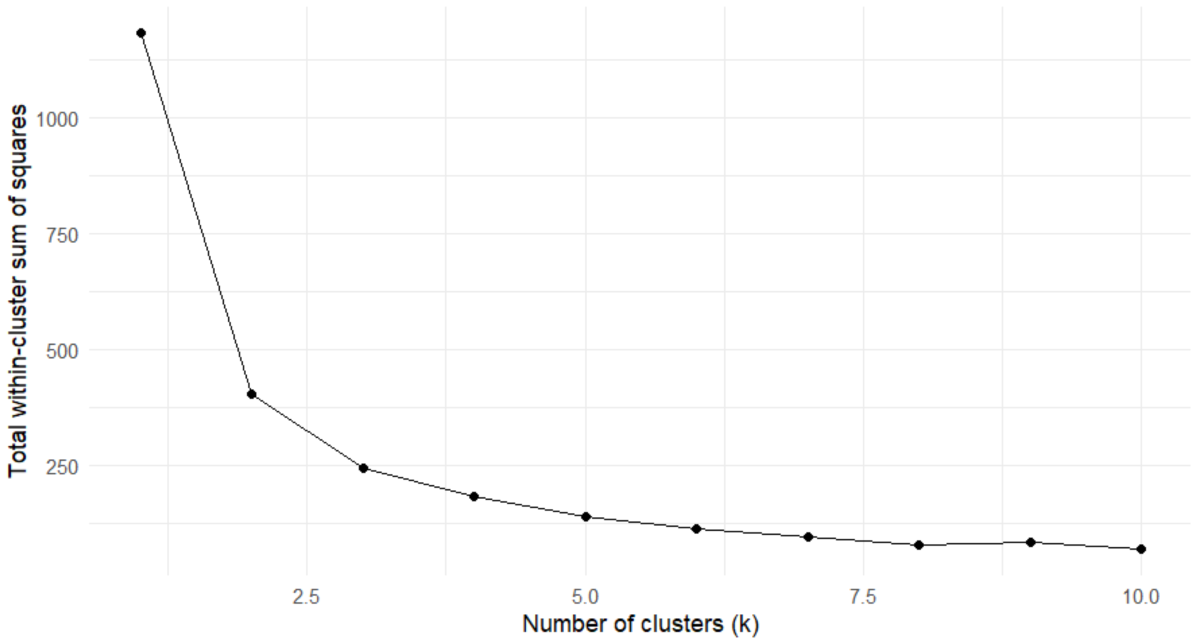
Elbow method platform A



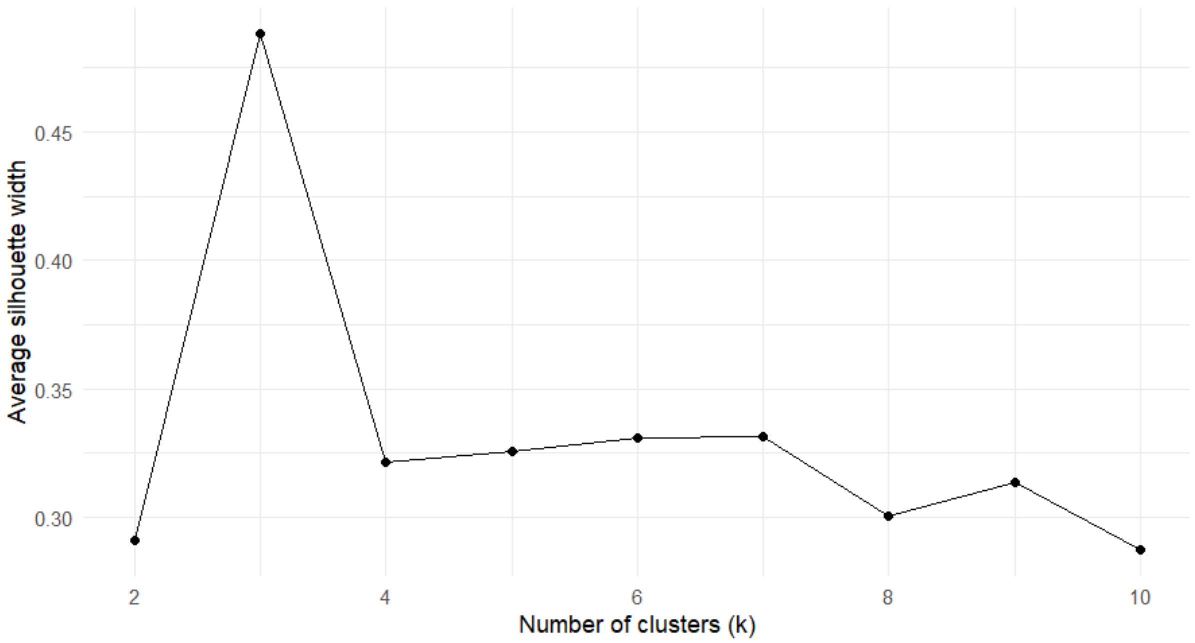
Silhouette method platform A



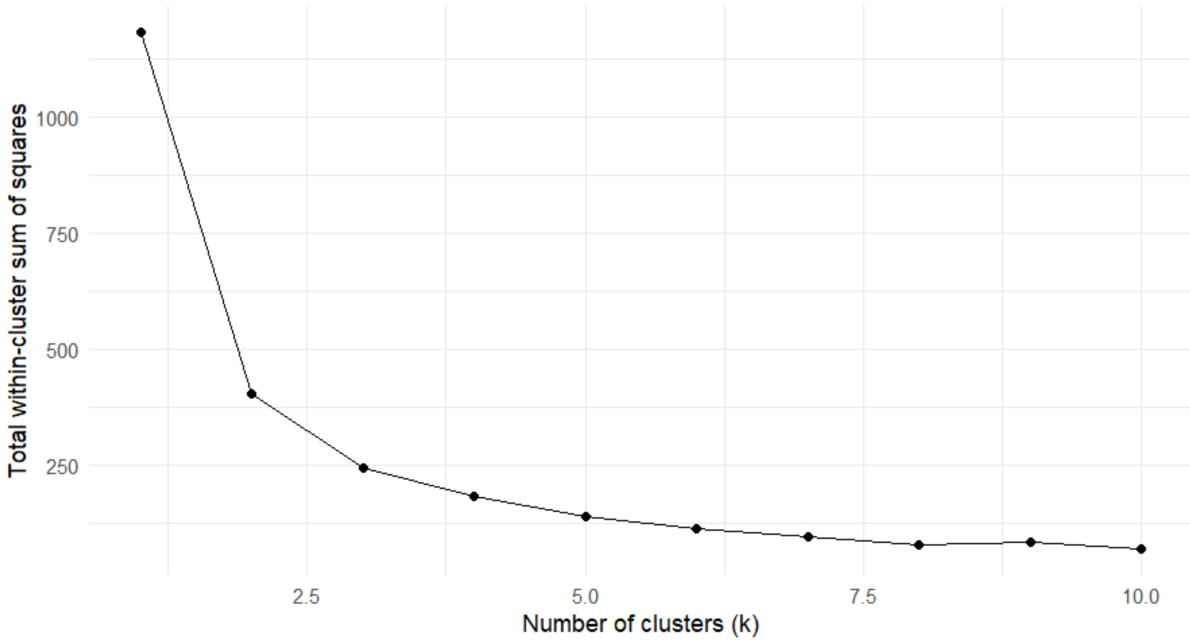
Elbow method platform B



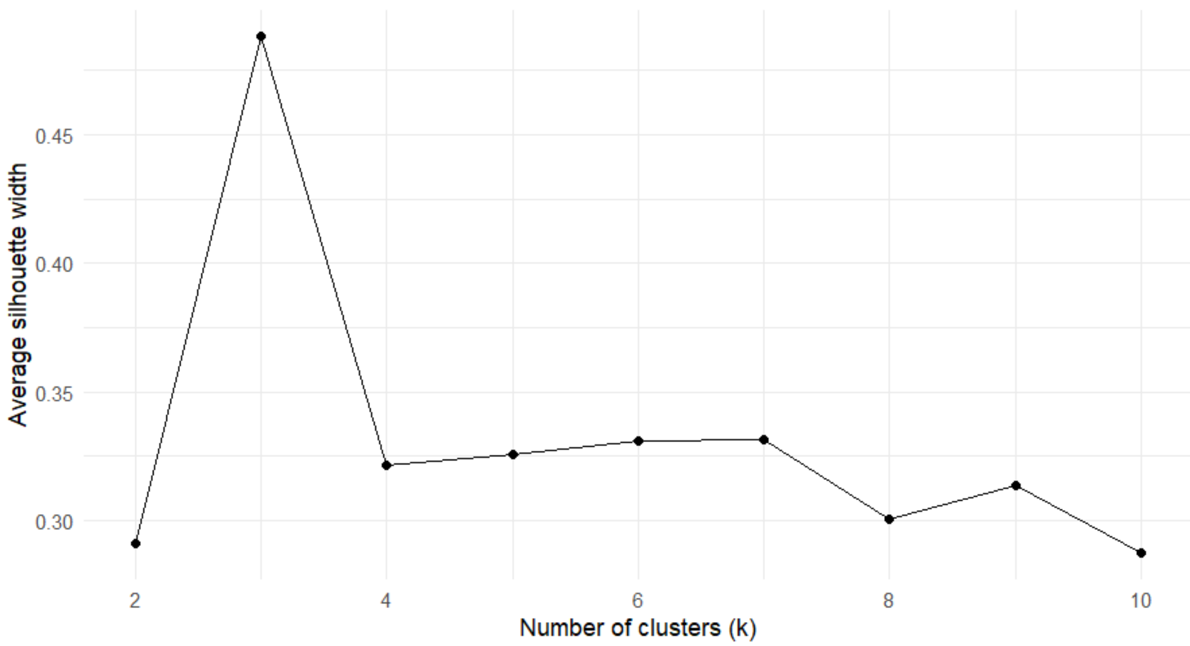
Silhouette method platform B



Elbow method platform C



Silhouette method platform C



Appendix C

Platform B

Principal component analysis

The PCA for platform B resulted in nine principal components, and four were retained with a cumulative variance explained of 83.4%. Variance explained per principal component can be found in figure 2. Table 6 shows the loadings for the different principal components, showing the different behaviour patterns represented by the components. PC1 had strong loadings on total actions and average actions per day, suggesting it represents overall usage intensity. PC2 showed positive loadings on interventions added and client accounts created, with negative loadings on video call started and feedback sent, representing administration versus communication preferences. PC3 had high loadings on organisation and days between first and last action, which suggests this component represents organisational usage patterns. PC4 had contrasting loadings on messaging versus video calls, indicating communication preferences.

Figure C1

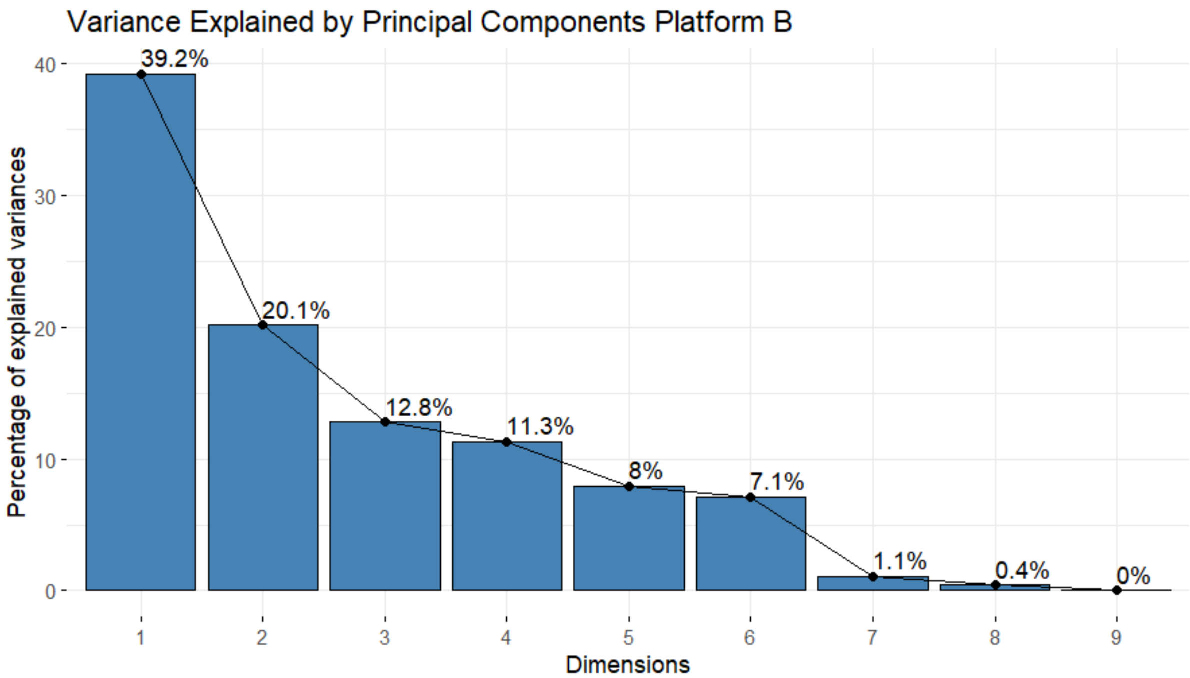


Table C1

Principal Component Loadings Platform B

	PC1	PC2	PC3	PC4
Organization			-.71	.35
Feedback sent	.40	-.41		
Message sent				.65
Videocall started		-.45		-.42
Intervention added		.49		-.43
Client account created	-.39	.43		
Total actions	-.51			
Days between first and last action		-.38	-.62	
Average number of actions per day	-.49			

Note. Values <0.3 omitted

The communalities for platform B can be found in table 7. Communalities ranged from .24 to .63. Organization showed the highest communality (.63). Total actions and average number of actions per day showed lower communalities, with .26 and .24, respectively. The remaining variables showed moderate communalities, ranging from .32 to .52.

Table C2

Communalities per variable in descending order

Variable	Communality
Organization	.63
Days between first and last action	.52
Intervention added	.43
Message sent	.42
Videocall started	.38
Client account created	.34
Feedback sent	.32

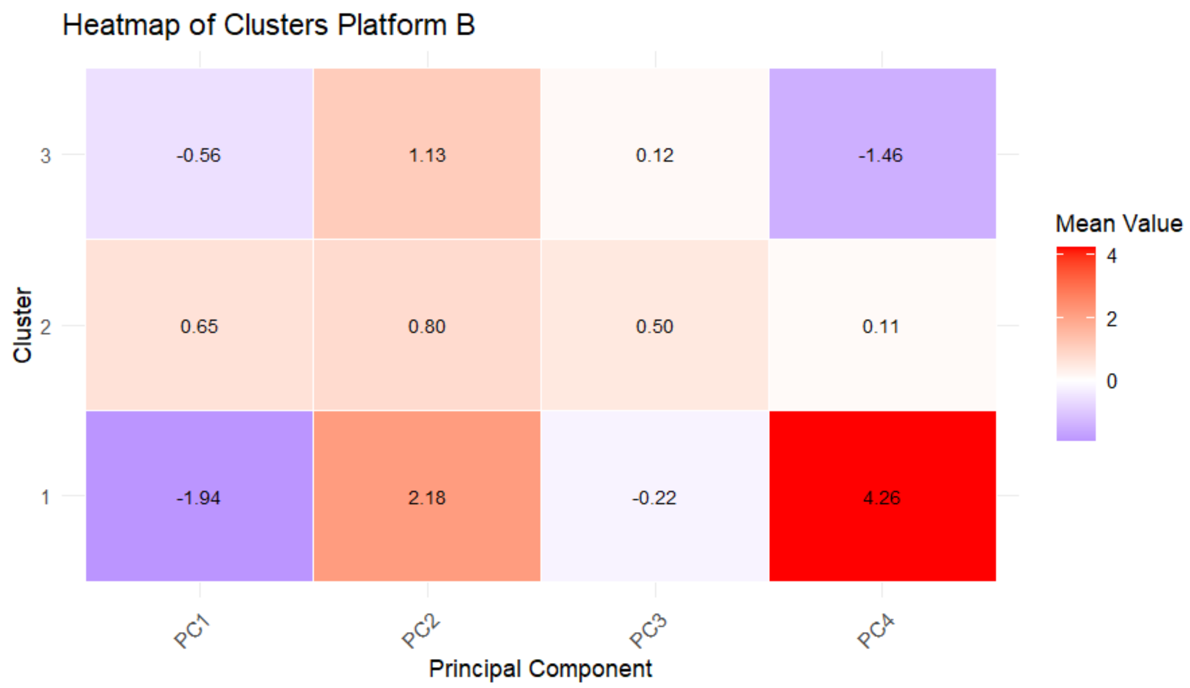
Total actions	.26
Average number of actions per day	.24

Cluster analysis

K-means clustering was done based on the principal components. Using the silhouette method, 3 clusters were identified as the optimal amount for analysis, which was supported by the elbow method. NbClust suggested k=2, and so silhouette width determined that k=3 had the more favourable outcome, showing reasonable separation between the clusters (n=.48).

The visualisation of clusters across the different principal component dimensions reveals distinct behaviour profiles among users of platform B, separated into three clusters. Cluster 1 comprised 1.6% of users (n=3), cluster 2 comprised 87% of users (n=160), and cluster 3 comprised 11.4% of users (n=21). When looking at the heatmap in figure 7, it shows that cluster 1 scores negatively on PC1, positively on PC2, negatively on PC3 and neutrally on PC4. This indicates that the cluster has varied activity levels, prefers administrative tasks, have occasional platform usage, and works across different organisations. Furthermore, cluster 2 scores positively on all principal components, indicating the cluster is active on the platform, preferring administration over communication, operates within specific organisational structures, and has a preference for messaging over video calls. Cluster 3 scored negatively on PC1 and PC4, and positively on PC2 and PC3, indicating lower activity levels, preferring administration-focused activities, with intermittent engagement patterns and varied organisational structures.

Figure C2



Platform C

The PCA of platform C resulted in nine components, of which five were retained with a cumulative variance explained of 87.7%. Variance per principal component can be found in figure 3. Component loadings indicate the contribution of each variable to the The first component has strong loadings on total actions, suggesting overall activity. PC2 shows preference for management activities. PC3 is likely a combination of interaction patterns and frequency/consistency, with strong loadings in organization, as well as feedback. In PC4, there is distinguished between brief, feedback-focused engagement and long term, less intensive intervention focused interactions. Lastly, PC5 represents synchronous vs. asynchronous communication patterns, with very strong loadings on videocalls, and negative loadings on messages sent.

Figure C3

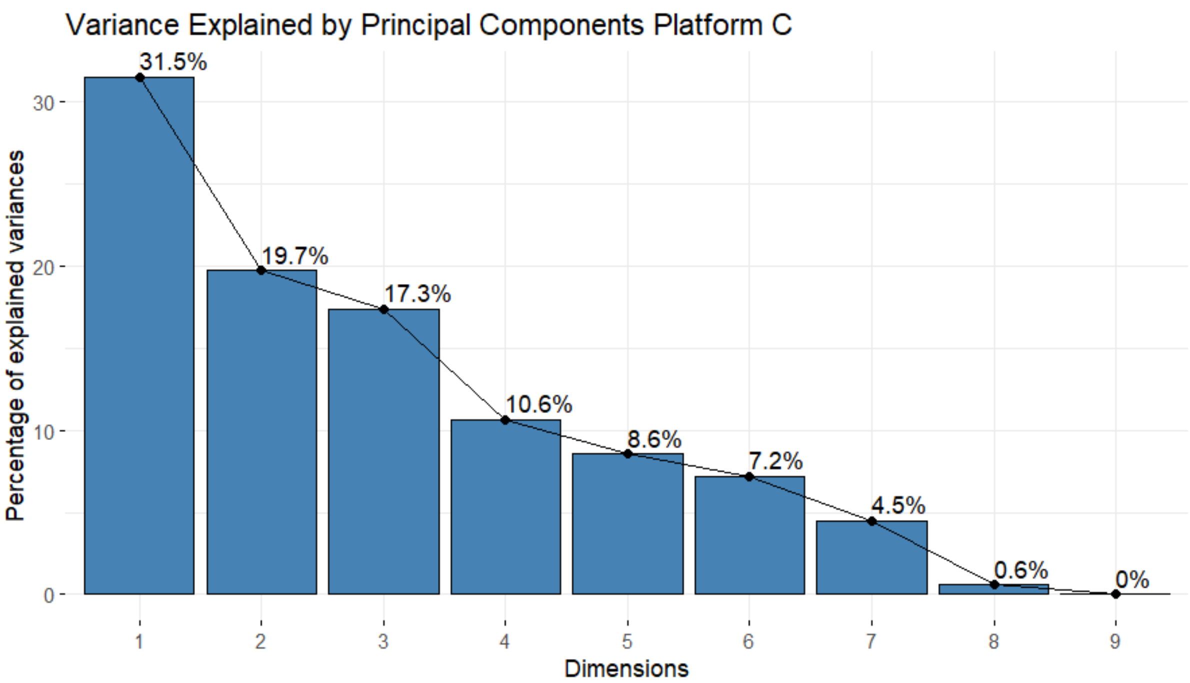


Table C3

Principal component loadings platform C

	PC1	PC2	PC3	PC4	PC5
Organization			-.58		.31
Feedback sent			-.52	.42	.39
Message sent		-.6			-.4
Videocall started		-.4	-.42		.68
Intervention added	.41			-.48	
Client account created	.4				
Total actions	.49	-.39			
Days between first and last action				-.64	
Average number of actions per day	.57				

Note. Values <0.3 omitted.

The communalities for platform C can be found in table 9. Communalities ranged from .16 to .8. Videocall started showed the highest communality. Client account created showed the lowest communality value with .16. The remaining communalities were moderate, ranging from .32 to .59.

Table C4

Communalities per variable in descending order

Variable	Communality
Videocall started	.8
Feedback sent	.59
Message sent	.51
Organization	.44
Days between first and last action	.41
Intervention added	.40
Total actions	.39
Average number of actions per day	.32
Client account created	.16

When comparing the principal component analyses of the three platforms, several differences appear. Platform A had 3 PCs, platform B 4 and platform C had 5 PCs, showing increasing usage differences between platforms. Based on the PCA, platform C had the most different types of users among the platforms, while users on platform A were most similar. This also showed in the cumulative variance explained, where 55.7% of the variance explained of platform A was done by PC1, this was only 31.5% on platform B. This again shows the greater complexity and diversity in usage between the platforms.

A similarity is that on all platforms, there was a principal component focused on user engagement intensity. This was shown by variables like total actions, and average actions per day.

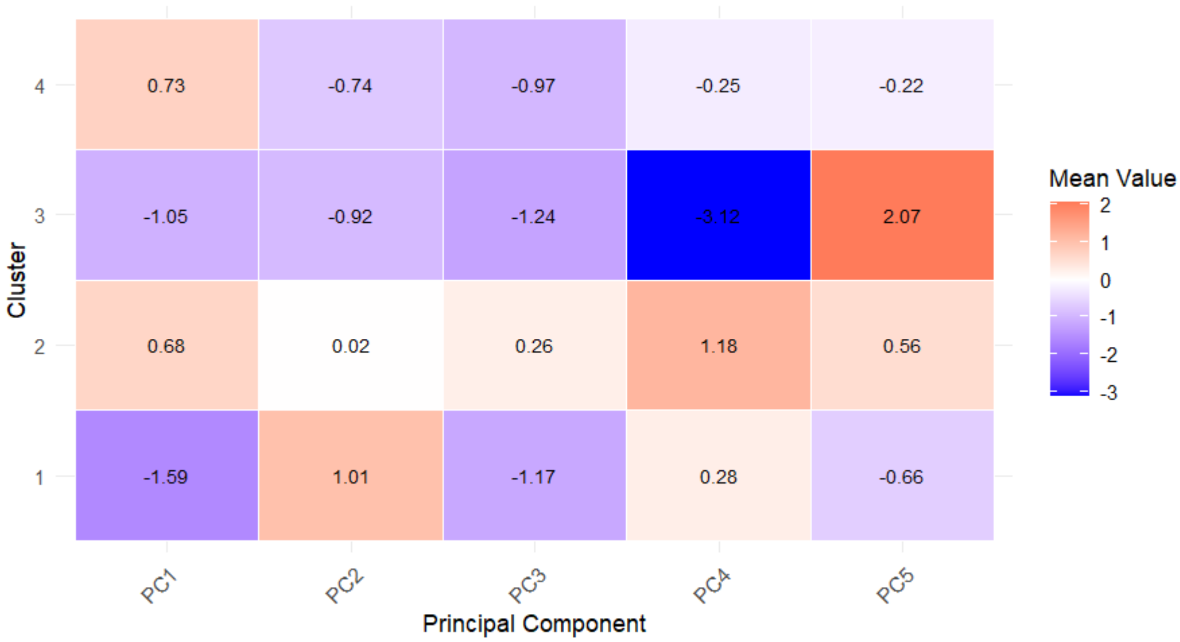
Platform C

The number of clusters used for platform C was once again decided using k-means clustering and running the silhouette test, elbow test and multiple other indices. Using the silhouette method, 3 clusters were initially identified, which was supported by the elbow method, however, the other tests suggested k=4. Comparing silhouette widths and variance explained, k=4 resulted in a more favourable outcome with a silhouette width of .72 and variance explained of 57%, suggesting well-separated clusters.

Cluster 1 comprised 4.7% of users (n=3), cluster 2 comprised 21.9% of users (n=14), cluster 3 comprised 3.1% of users (n=2), and cluster 4 was the biggest with 70.3% of users (n=45). When looking at the heatmap, it shows that cluster 1 scores negative on PC1, PC3 and PC5, and positive on PC2 and PC4, indicating this cluster has low overall activity levels, prefers administrative actions, belongs to organisations, engages in brief feedback-focused activities and prefers asynchronous communication. Cluster 2 scored positively on all principal components, with a neutral positive score on PC2, indicating moderate to high activity levels, balanced communication and administration preferences, belongs to an organisation with distinct usage patterns, engages in brief feedback-focused activities, and prefers synchronous communication. Cluster 3 scored negatively on PC1, PC2 and PC3, and strongly positively on PC4 and PC5, indicating low activity levels, a strong preference for communication, does not belong to organisations with usage patterns, only uses the platform for a short time and has a very strong preference for synchronous communication. Cluster 4 only scored positively on PC1, indicating high overall activity, strong preference for communication activities, belongs to organisations with less distinct patterns, engages in long term intervention focused activities, and prefers asynchronous communication over synchronous communication.

Figure C4

Heatmap clusters platform C



Appendix D

Table D1

	Platform used	DMHI platform usage	Type of mental health professional	Internet proficiency	Usage pattern	Facilitators	Barriers
1	Platform A		Basic psychologist	"Pretty good"	Mostly through the platform	More tools to your disposal Monitoring clients	Integration with other systems Technical problems
2	Platform B	Blended	Basic psychologist	Good	Support for treatments	More tools to your disposal	Limited availability of some questionnaires
3	Platform C	Fully online	Mental health nurse specialist	Good	Mostly through the platform	Combination of live chatting and writing Monitoring clients	Technical problems
4	Platform A	Fully online	Basic psychologist	"Quite high"	Fully online	Monitoring clients	Technical problems Integration with other systems

5	Platform B	Blended	Psychologist	"I think good"	Support for treatment	Evidence based programmes Monitoring clients	Limited availability of some questionnaires
6	Platform B	Blended	Psychologist	"I feel very comfortable with digital methods"	Partly online, partly face-to-face	Improved communication with clients	Technical problems System integration
7	Platform C	Blended	Psychologist	I feel competent, but not as on top of it as I want to be	Base in all therapies	Tailored content Monitoring clients	Technical problems