Users' attitude towards adding human feedback when preparing for quitting smoking/vaping with a virtual coach: A mixed-methods analysis

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Abstract

Smoking and vaping cessation remains a significant public health challenge despite the availability of numerous aids and eHealth applications. This study explores the reasons behind users' preference for human feedback when preparing to quit smoking or vaping, aiming to address a gap in existing literature on the integration of human elements in eHealth platforms. The research involved 479 participants interacting with a virtual coach, with some receiving human feedback. We conducted a thematic analysis of two open-text questions with 265 responses each from post-questionnaires, and key themes such as emotional connection, personalized advice, effectiveness, motivation, and accountability were identified. Through using quantitative data and previously published research, these findings were further explained. The results from the quantitative analysis show that incorporating human elements in eHealth applications can enhance smoking cessation support. This research provides insights into the main reasons how the human support in eHealth applications should be designed. Key recommendations include designing human feedback to offer empathy and validation, tailoring feedback to individual needs, incorporating interactive elements to maintain engagement, providing constant encouragement, and establishing accountability mechanisms.

1 Introduction

Smoking remains one of the leading causes of preventable diseases and premature death globally [19]. Despite widespread public health campaigns and the availability of numerous cessation aids, many individuals struggle to quit smoking [22]. Given that the motivation to quit smoking typically originates from a personal himself and that smoking cessation represents a lifestyle change, there is a vital need for ongoing social support [4]. Support from family, friends, and health professionals can significantly enhance an individual's ability to quit by providing encouragement, accountability, and personalized advice [10].

In recent years, health services provided via the Internet and various other technologies, known as eHealth, have demonstrated their potential to offer this essential social support [6]. These technologies have the potential to transform traditional smoking cessation methods by providing scalable, cost-effective solutions that are accessible to a broader population. Studies, such as those by Paridhi et al. [25] and Maenhout et al. [15], have explored automated coaching programs for smoking cessation, showcasing their potential to enhance motivation and adherence among users. Additionally, a recent study [27] on the design features of embodied conversational agents in eHealth highlights how these features can improve user engagement and health outcomes. Previous research [8] shows that eHealth applications have brights future, however the question of whether a human element is beneficial in the applications is still not answered. There is a gap in the literature concerning the role and impact of human feedback in smoking cessation processes facilitated by eHealth applications. Our study aims to address the gap in the literature by investigating why users prefer to receive human feedback during the smoking cessation process.

A text-based virtual coach named Kai was developed by the interactive intelligence group at the intelligent systems department of TU Delft to help smokers quit by performing various activities [3]. Albers and Brinkman conducted an experiment involving 479 participants interacting with the virtual assistant. The study contains the filling of a pre-questionnaire, five sessions with the virtual coach and a post-questionnaire. After each session, one-fifth of the participants were introduced to a human coach who gave them feedback.

Our task is to understand and analyze the data gathered by this experiment and find reasons why people prefer to receive human feedback during the smoking cessation process and its implications. To do this, a mixed-method analysis is performed to answer the question: "What are users' reasons for wanting feedback from a human coach when preparing for quitting smoking/vaping?". Understanding these reasons can provide insights into how eHealth platforms can be designed to support smokers through the quitting process more effectively.

Six-step thematic analysis [12] was applied to the free-text responses of two questions from the post-questionnaire (265 responses per question). The data was obtained from the experiment conducted by Albers and Brinkman. The results of the analysis were themes which correspond to the main reasons why people prefer human feedback during the smoking cessation process. After finding the reasons, triangulation with the quantitative data as described by Peersman [23] was performed to gain further insights into the themes. Furthermore, a triangulation with literature is performed to validate the results. After each theme found recommendations based on the findings are given.

Our study found that the participants valued human feedback during the smoking cessation process for several reasons. They appreciated the emotional connection and support, personalized feedback, the interactive nature of human feedback, the encouragement and motivation from human coaches and the accountability towards them. Through the literature study, these results were supported and the quantitative analysis showed positive correlation between the found themes and user characteristics such as accountability, effectiveness, engagement and the intent to continue the smoking cessation journey using human feedback.

2 Methodology

This study employs a mixed-methods approach to explore the reasons why participants prefer to obtain human feedback during the smoking cessation process. The approach is inspired by the thematic analysis described by Kiger and Varpio [12]. Thematic analysis was selected due to its flexibility, capacity to offer detailed insights, and effectiveness in uncovering patterns and themes within qualitative data. Additionally, its systematic approach to coding and theme development enhances transparency and reproducibility, ensuring the analysis is both clear and methodical. Thematic analysis can also be easily integrated with quantitative methods, allowing us to triangulate findings and strengthen the overall validity of our research.

2.1 Participant recruitment and data collection

Albers and Brinkman gathered the data using the online recruitment platform Prolific [2]. The experiment conducted by them received approval from the TU Delft University Human Research Ethics Committee (Letter of Approval number: 3683). A number of people were recruited via the platform and received remuneration for their efforts. A pre-screening questionnaire was employed to define the eligibility of the participants in the experiment. The eligible participants for the study were fluent in English, smoked tobacco products or vaped daily, and had not participated in previous studies on quitting smoking using a virtual coach to avoid overlapping activities. The mean age was 36.0, where the largest age group of participants was 26-33 years old, making up 30.4% of all, followed by those aged 18-25 (20.2%) and 34-41 (21.3%). The gender distribution is almost evenly split between men and women, with men at 49.4% and women at 49.0% of all people included. The educational background of the participants varied from no formal qualifications to doctorate degrees. A pie charts of the user characteristics could be found in the Appendix A. Those who qualified were then asked to complete a pre-questionnaire. After it, the participants took part in five sessions with the virtual coach, named Kai. During these sessions, the virtual coach suggested preparatory activities in order to increase the physical activity of the participants and encourage them during the smoking cessation process. One-fifth of the people received feedback from an expert after the first four sessions based on their completed activities and a short introduction given by them during the sessions. They received personalized feedback from human coaches with psychology backgrounds, who provided support, suggestions, and reinforcement based on the participants' smoking/vaping history, activity experiences, and self-efficacy ratings as well. The feedback was delivered via Prolific between sessions. After completing all sessions, the participants were asked to fill a post-questionnaire. It asked for information about the participants' smoking or vaping frequency, their self-identity as quitters, and their weekly exercise amount. It also measured their perceptions of the virtual coach and rated the effect of human feedback on their preparation for quitting.

2.2 Thematic analysis

The thematic analysis was conducted following the structured six-step process outlined by Kiger and Varpio [12], which is designed to ensure comprehensive and systematic handling of qualitative data.

Familiarization with the Data

The first step in a thematic analysis is to get acquainted with the data. We are interested in two questions from the post questionnaire and, namely, whether the participants prefer to follow the preparation course with/without human feedback and how the human feedback affected them while preparing for quitting smoking/vaping. Each question had 265 free-text responses. This step was completed by reading through all responses twice while noting ideas for potential codes. This is essential for understanding the content, noting initial ideas, and beginning to identify patterns that may emerge [5].

Generating Codes

The second step is to generate codes. In this study, several rounds of code generation and refining were conducted. During the first round of coding, the codes were inductively generated from the data by deriving them from all responses. This approach led to a significant number of codes, which indicated that code refinement was needed. Subsequently, several codes were merged into one, with the cause being that they are synonyms or overlap by meaning. An example of this process is merging the codes "understanding" and "caring" into a single code name "understanding". At the beginning, the number of codes was over fifty, after three rounds of refinement, the final coding scheme consisted of 25 different codes. At the same time, the top 22 most occurring ones accounted for approximately 98,9% of the coded data. An important fact to note is that not all data could be classified to the coding scheme as there were irrelevant to the study answers, which didn't match any of the codes, and were not useful for the purpose of this study. Examples of such answers are "I think it was a good study" (P558) and "I have no opinion on this" (P178). The number of these responses was 78 or 14.71% of all data.

To check for the reliability of the scheme and to reduce researcher bias, a second coder was introduced. He was given definitions of the codes, which can be found in Appendix B and was trained on 20 samples of the data in order to obtain an idea of how the coding is applied. After the second coder coded all the data, the Cohen's Kappa was calculated, and the level of agreement was checked. The result was approximately 0.825 using the weighted average Cohen's Kappa of all codes with the corresponding weights, which indicates almost perfect agreement [17]. The Cohen's Kappa for each code and the number of their occurences can be seen in Appendix C. After calculating the Brennan-Prediger kappa, the observed agreement was 0.828, which indicates the proportion of times the two coders agreed on their coding. The Brennan-Prediger's kappa itself was 0.821, indicating an almost perfect level of agreement between the coders [17]. Because of the results, no changes to the coding scheme were made.

Searching for Themes and Reviewing them

The final steps of the process include searching for themes as well as improving and naming them. As mentioned by Kiger and Varpio [12], finding themes and refining them is an iterative process. The themes were devised from the final coding scheme. A second coder was employed to analyze the effectiveness again. He was given a set of theme names, as well as all final codes and their definitions. His task was to assign each code to the corresponding theme. If not all codes were assigned as by the original coder, a short discussion and theme refinement were conducted. After two rounds, the two coders agreed on the codes' distribution among the themes and their naming. The final step of the process was to create a thematic map, which is shown in Fig.1.

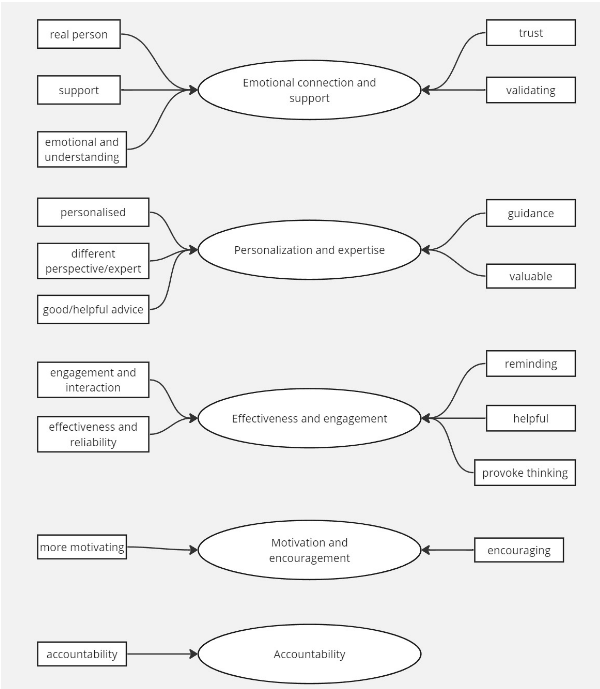

Figure 1: Thematic map of all themes found by the analysis.

2.3 Method analysis

To analyze the previously found themes, a method triangulation was performed. It included quatitative data analysis as well as literature study in this field.

Before conducting the quantitative analysis, the needed data was extracted from the questionnaires. Quantitative data about the perception of the human feedback was extracted, which was later used to support the findings of this study. The analysis code used, together with the results, can be found in the 4TU Research database [21].

The goal of the literature study was to validate our findings by findings on similar topics to the research field. Those findings were used to support the previously found themes. For example, papers about perception of human feedback, its implications and human behaviour were taken into account. A keyword and references search was utilized via Scopus to search for appropriate literature. The keywords used were ehealth, smoking, cessation, human, improvement and feedback.

3 Findings and triangulation

In the next subsections, the themes found by the thematic analysis will be explained and further supported by the literature study and quantitative analysis.

3.1 Emotional connection and support

This theme highlights the importance of human interaction in providing emotional support, understanding, and trust during the smoking cessation process. Some participants highly valued the feedback received from a real person because it offered empathy and validation, which they found vital in their efforts to quit smoking. "It was easier because I felt less alone and more understood by a real person" (P288). "it showed empathy for the cause, which is very important when deciding to trying to quit an addiction" (P663). Feeling understood and emotionally supported can increase an individuals' determination and ability to follow their smoking cessation plan, making the journey less exhausting. Understanding why users value emotional connection and support and how it relates to their process of quitting smoking can help in designing eHealth application that can replicate and incorporate these human elements in order to enhance their effectiveness.

This theme represents about 18.7% of the total codes, amounting to 86 responses. Table 2 illustrates the codes included in this theme and their corresponding contributions in percentages.

Code	**Contribution (%)**
Real person	35.61
Emotional and understanding	31.06
Support	22.73
Trust	9.09
Validating	1.52

Table 1: Contribution of codes to the theme Emotional Connection and Support

The literature study revealed that previous studies noticed the impact of emotional support in health contexts. The study by Balmford et al. [4] shows the significant impact of personalized interactions on the smoking cessation process, showing that emotional support leads to better outcomes. His findings were that the users of an automated interactive, personalized coaching program who received supportive, human-like interactions were more likely to succeed in quitting smoking. Furthermore, the meta-analysis by Rains and Young [24] explores the role of supportive communication in health contexts. It concludes that emotional support is a crucial component of effective health interventions, enhancing the emotional well-being and increasing the chances of successful behaviour change.

Recommendation

The findings suggest that human feedback offering emotional support and understanding can be valuable for users during the smoking cessation process. It might be beneficial for eHealth applications to include human elements that provide empathy and validation, making users feel understood and less alone.

3.2 Personalization and Expertise

This theme reflects the value of feedback that is specifically tailored to the needs of the participants and the expert knowledge that human coaches bring. The participants perceived the personalized feedback as more relevant and effective in supporting them during the smoking cessation process. The insights and advice offered by the experts are considered more applicable, credible and valuable. "The human coach gave personalized advice that was very relevant to my specific situation" (P241). "I appreciated the expert perspective, which made the advice more valuable and reliable" (P155). The experts' guidance enhanced the experience of the participants during their plan of quitting smoking. This theme emphasizes the need for tailored interventions in eHealth platforms, showing that generic advice is less effective than a personalized one. Personalized and expert feedback can more effectively address individual challenges, making it easier for individuals to follow their smoking cessation plans.

This theme comprises approximately 20.2% of the total codes, corresponding to 93 responses. Table 3 shows the codes included in this theme and their corresponding contributions in percentages.

Code	Contribution (%)
Personalised	43.02
Different perspective/expert	25.58
Good/helpful advice	15.12
Guidance	11.63
Valuable	4.65

Table 2: Contribution of codes to the theme Personalization and Expertise

The study by Maenhout et al. [16] highlights that personalized feedback via chatbots significantly improves engagement in adolescent health promotion activities. According to it personalization leads to better engagement and outcomes by directly addressing the specific needs and circumstances of the individuals. The importance of personalized feedback in health interventions is also highlighted in the research by Ghantasala et al. [26]. It underscores the effectiveness of personalized messaging in promoting behavioural changes and increasing motivation.

Recommendation

The theme of personalization and expertise indicates that tailored feedback from human coaches is perceived as more relevant and effective by users. Therefore, eHealth applications should incorporate personalized feedback that is specific to the individual's smoking history, challenges, and progress.

3.3 Effectiveness and Engagement

This theme covers the practical benefits of human feedback, including enhanced engagement, interaction, and perceived effectiveness of the feedback received during the smoking cessation process. Participants felt that human feedback made the cessation process more engaging and enjoyable, which helped them maintain their commitment to the process. The human coaches provoke deeper thinking about the quitting process, serve as reminders of the goals and increase the reliability and effectiveness of the application. "I found the human feedback very helpful in staying on track and being reminded of my goals" (P241). "The human coach made the sessions more engaging and interactive, which kept me motivated" (P49).

This theme covers around 20.2% of the total number of codes, or 93 responses. Table 3 depicts the codes this theme consists of and their corresponding contributions to the theme in percentages.

Code	Contribution (%)
Helpful	43.01
Engagement and interaction	22.58
Provoke thinking	13.98
Reminding	10.75
Effectiveness and reliability	9.68

Table 3: Contribution of codes to the theme Effectiveness and Engagement

Eysenbach's research [6] into eHealth interventions found that those incorporating interactive and engaging elements are more likely to succeed in achieving behaviour change. The study highlights the importance of engagement in maintaining user interest and commitment to health interventions. Furthermore, the study by Morrison et al. [20] observed higher engagement levels in eHealth programs that included human elements.This shows that human interaction components in digital health interventions lead to better user engagement and effectiveness in achieving health goals.

Recommendation

Human feedback appears to enhance engagement and interaction during the smoking cessation process. To maintain user interest and motivation, eHealth platforms could consider integrating interactive elements in their feedback process. This might include regular check-ins, goal-setting sessions, and activities that provoke deeper thinking about the quitting process.

3.4 Motivation and Encouragement

This theme highlights that people value the encouragement and motivation to quit smoking received from the human feedback. Participants felt that human interaction was more encouraging and motivating than automated feedback. "The human feedback was very encouraging and kept me motivated throughout the process" (P49). "I felt more motivated to quit smoking with the constant encouragement from the human coach" (P241). Encouragement from a human coach helps sustain motivation, which is crucial for overcoming the challenges associated with quitting smoking [13].

This theme encompasses approximately 7.2% of the total codes, amounting to 33 responses. Table 4 illustrates the codes comprising this theme, along with their respective percentage contributions.

West and colleagues found that encouragement from health professionals significantly increases motivation for smoking cessation, highlighting the role of motivational support in helping individuals stay committed to their quit-smoking

Code	Contribution (%)
Encouraging	51.52
More motivating	48.48

Table 4: Contribution of codes to the theme Motivation and Encouragement

plans [28]. Furthermore the clinical practice guideline by Fiore et al. emphasizes the role of motivational interviewing and encouragement in smoking cessation programs, finding that such interventions significantly enhance the likelihood of successful smoking cessation [7].

Recommendation
The theme of motivation and encouragement highlights the importance of constant support in sustaining users' motivation to quit smoking. eHealth applications might benefit from incorporating human feedback that provides regular encouragement and positive reinforcement. Celebrating small victories and offering constructive feedback on setbacks could be effective strategies to keep users motivated throughout their quitting journey.

3.5 Accountability

This theme is represented by accountability, indicating that having someone to report to can impact the success of quitting efforts. Participants felt more accountable when they received feedback from a human coach. Knowing that they had to report their progress to a real person enhanced their commitment to sticking to their cessation plans. "Knowing that I had to report back to a human coach kept me accountable and on track" (P49). "The human coach held me accountable, which was critical for my success" (P241). This highlights the need for such features in eHealth interventions. The presence of an accountability mechanism helps ensure that individuals remain committed to their goals and make consistent progress [14].

This theme consists of only one code, namely accountability, which contributes to 2.8% of all codes, or 12 responses.

The meta-analysis by Harkin et al. [9] identified accountability as a key factor in successful behavior change interventions. The researchers found that monitoring and reporting progress significantly enhances the likelihood of achieving health goals. Karoly's work [11] on self-regulation mechanisms highlights the importance of accountability in maintaining long-term behavior changes, including smoking cessation. The study [11] suggests that accountability mechanisms are crucial for ensuring sustained commitment and progress.

Recommendation
Incorporating mechanisms for accountability in eHealth interventions might be useful. This could involve scheduled feedback sessions where users report their progress to a human coach.

3.6 Quantitative analysis

Near the end of the post-questionnaire the participants that received human feedback were asked to rate their experience with it. Namely, they had to rate whether they would rather have followed the preparation course with or without the feedback from the human coach, whether the human feedback affected their preparation for quitting positively, whether the human coach affected their feelings of accountability towards the preparation course and whether the human coach affected their engagement with the preparation course. The scale was from -5 to 5, with -5 indicating that the human feedback had a negative effect and 5 being that the feedback had a positive effect. After trying to correlate the found themes with these results, the following correlations and their p-values were found as shown in Tables 5-9.

The themes were represented as arrays filled with values 0 or 1, where one means that the theme is present and zero means it is missing for a participant. An alpha level of 0.05 was used to determine whether the correlation significantly deviates from zero, with p-values less than 0.05 indicating statistical significance. Spearman's correlation coefficients were interpreted as in the first table by Haldun Akoglu [1], according to Dancey & Reidy, since our field of research in psychology.

Variable	Spearman Correlation	p-value
age	-0.11	0.089
engagement	0.24	$<$0.001
accountability	0.25	$<$0.001
positive effect	0.31	$<$0.001
intent to continue	0.31	$<$0.001

Table 5: Spearman Correlation Coefficients and p-values for theme Emotional connection and support correlated with a subset of user variables

The weak correlations from Table 5 indicate that participants who value human feedback as more emotional reported higher engagement, accountability, perceived effectiveness, and preference for human feedback in their quitting process. Since the negative correlation with age is insignificant, no conclusions can be drawn.

Variable	Spearman Correlation	p-value
age	0.09	0.168
engagement	0.16	0.009
accountability	0.26	$<$0.001
positive effect	0.24	$<$0.001
intent to continue	0.24	$<$0.001

Table 6: Spearman Correlation Coefficients and p-values for theme Personalization and Expertise correlated with a subset of user variables

Those who appreciated the personalized and expert feedback reported higher engagement, accountability, effectiveness, and a preference for human feedback, according to Table 6.

Variable	Spearman Correlation	p-value
age	0.04	0.547
engagement	0.19	0.002
accountability	0.15	0.019
positive effect	0.24	<0.001
intent to continue	0.25	<0.001

Table 7: Spearman Correlation Coefficients and p-values for theme Effectiveness and Engagement correlated with a subset of user variables

The results from Table 7 indicate that participants who felt the intervention was effective and engaging due to the human element were, in fact, more engaged, felt more accountable, perceived the intervention as more effective, and preferred to continue the smoking cessation process with human feedback.

Variable	Spearman Correlation	p-value
age	0.02	0.713
engagement	0.17	0.005
accountability	0.18	0.003
positive effect	0.25	<0.001
intent to continue	0.19	0.003

Table 8: Spearman Correlation Coefficients and p-values for theme Motivation and Encouragement correlated with a subset of user variables

The same applies to the people who find human feedback to be more motivating and encouraging, reported higher engagement, accountability, effectiveness, and preference for human feedback as shown in Table 8.

Variable	Spearman Correlation	p-value
age	0.12	0.059
engagement	0.05	0.467
accountability	0.02	0.750
positive effect	0.01	0.882
intent to continue	<0.01	0.961

Table 9: Spearman Correlation Coefficients and p-values for theme Accountability correlated with a subset of user variables

The absence of significant correlations with the quantitative measures. as visible in Table 9, indicates that while accountability is important, it might not be directly measurable with the variables used in the questionnaire.

The quantitative analysis of our study explored the relationships between all themes and quitter self-identity based on items from Meijer et al [18], the smoker frequency and the amount of weekly exercises, which are measured on a Likert scale from 1 to 5. Quitter self-identity was composed of 3 items based on Meijer et al. [18], after calculating their Cronbach alpha, a result of 0.78 emerged, which indicated acceptable consistency among them. Therefore we decided not to correlate these user characteristics separately, but rather to use their mean. The findings revealed that the correlations between these themes and the variables were generally weak and non-significant Tables. 10, 11, 12, 13, 14. For instance, while the theme of emotional connection and support showed a weak positive correlation with quitting self-identity (r = 0.17), the p-value (0.077) indicated a lack of statistical significance. Similarly, personalization and expertise, effectiveness and engagement, motivation and encouragement, and accountability all demonstrated weak correlations with the smoking-related variables and weekly exercise, none of which were statistically significant.

Variable	Spearman Correlation	p-value
Quitter self-identity	0.17	0.077
Smoking frequency	-0.12	0.221
Weekly exercises	0.07	0.464

Table 10: Spearman Correlation Coefficients and p-values for theme Emotional connection and support correlated with a subset of user characteristics

Variable	Spearman Correlation	p-value
Quitter self-identity	0.07	0.441
Smoking frequency	0.10	0.271
Weekly exercises	0.06	0.546

Table 11: Spearman Correlation Coefficients and p-values for theme Personalization and Expertise correlated with a subset of user characteristics

The absence of significant correlations implies we found no support for any associations. Future work could explore these variables further in depth.

4 Responsible Research

This research is based on data gathered by Albers and Brinkman, during an experiment conducted by them, which received approval from the TU Delft University Human Research Ethics Committee (Letter of Approval number: 3683) [2]. In order to prevent falsification, the data was not altered at any point and only extracted from the post-questionnaire.

The participants in the study were recruited using the online platform Prolific. All of them satisfied an inclusion criteria which can be seen in the pre-screening questionnaire. An advantage of using Prolific is that the participants are well diversified - they are from all over the world, which prevents data bias towards a race, gender or age. A drawback is that they are paid for participating in the experiment. This could lead to increased motivation to finish the questionnaires, while giving answers with minimal effort, which influences how trustworthy the answers are.

During the whole research process, the handling of personal data was involved. Therefore, it was important not to share the data with anyone except the people in the research group. For this to happen, a team on Microsoft Teams was

Variable	Spearman Correlation	p-value
Quitter self-identity	0.09	0.329
Smoking frequency	0.10	0.283
Weekly exercises	-0.12	0.207

Table 12: Spearman Correlation Coefficients and p-values for theme Effectiveness and Engagement correlated with a subset of user characteristics

Variable	Spearman Correlation	p-value
Quitter self-identity	0.06	0.500
Smoking frequency	-0.06	0.549
Weekly exercises	-0.10	0.265

Table 13: Spearman Correlation Coefficients and p-values for theme Motivation and Encouragement correlated with a subset of user characteristics

formed, and all the data was shared in the shared folder there. This ensured that the data was not accessible from outside our team. Sensible personal information was removed, our supervisors anonymised the dataset before giving us access to it. In this way, we did not handle any sensitive personal information such as names. This minimised the risk of data leakage as well.

An essential aspect of conducting responsible research involves maintaining transparency, this ensures that the study can be reproduced by following the steps described in the paper. Therefore all steps made during the research project are described in detail in Section 2. Furthermore, the data of the second coder, the Python scripts and intermediate results are uploaded to the 4TU ResearchData [21] repository with detailed instructions on how they can be used. In this the whole research process and the data used in it adhered to the FAIR principle[29].

Several measures were taken into account to eliminate personal bias. In the coding process, a second coder was trained and coded the data in order to ensure the reliability of the scheme. This approach was also used in the process of defining the themes. Finally, triangulation with the quantitative data and literature was performed.

When reporting the results, both statistically significant and non-significant outcomes were presented. Displaying only statistically significant results would have been cherry-picking, which is considered a bad practice.

5 Discussion

The findings of this study reveal that users prefer human feedback when preparing to quit smoking or vaping because it provides essential emotional support, personalized advice, enhanced engagement, motivation, and accountability. Participants valued the empathy, understanding, and validation from human coaches. Personalized feedback was seen as more relevant and effective in addressing individual needs, while interactions with human coaches made the process more engaging. Regular encouragement and positive reinforcement from human coaches, sustained motivation, and the need to report progress to a real person increased adherence to cessation plans. These insights answer the research question by highlighting that human feedback offers the emotional, personalized, engaging, motivational, and accountability support necessary to enhance the effectiveness of eHealth applications for smoking cessation.

Variable	Spearman Correlation	p-value
Quitter self-identity	0.02	0.852
Smoking frequency	-0.12	0.199
Weekly exercises	-0.02	0.821

Table 14: Spearman Correlation Coefficients and p-values for theme Accountability correlated with a subset of user characteristics

This research relied on pre-collected data. During the quantitative analysis, it was found that some participants had not completed all questionnaire entries. However, using pre-collected data allowed the research to be conducted within a limited timeframe.

The sample size was relatively big (479 participants), however it may not represent all age groups and races. Furthermore, the data which the participants self-reported could be biased. Additionally, the use of an online recruiting platform could introduce biases, as participants were likely more comfortable with technology. All the previous factors could have influenced the reliability of the results.

In our study, we used Spearman's correlation coefficient to explore the relationships between the identified themes and various user characteristics. Spearman's coefficient is particularly useful for non-parametric data and is effective in identifying monotonic relationships. However, it does have some limitations, such as being less sensitive to the strength of relationships compared to Pearson's correlation coefficient, which assumes linear relationships and requires normally distributed data.

Efforts to reduce the researcher bias were put into this study, namely the use of a second coder for the codes and the themes during the thematic analysis. The second coder helped increase the reliability of the coding scheme, as described in Section 2.2. Ideally, if time allowed, an additional round with third coder could have reduced the bias further. The same applies to the verification process of the themes. The quantitative data was used to triangulate our qualitative findings and to gain further insights into them. Furthermore, the findings are supported by literature as well. All these approaches helped to increase the reliability of the study and minimize the bias.

6 Conclusions and Future Work

This study explores what are the reasons for people to prefer to have human feedback during the smoking cessation process. By employing a mixed-methods approach, we identified several key themes that explain why participants value human feedback in combination with automated coaching.

These themes include emotional connection, personalization, effectiveness, motivation, and accountability.

The findings reveal that people value the emotional connection that automated systems cannot replicate,the human feedback is providing users with support, empathy, and building trust. Participants find personalized feedback from human coaches to be more relevant and effective in meeting their individual needs Additionally, they highlight that human feedback enhances their engagement and motivation, making the cessation journey more interactive and enjoyable. The accountability provided by human interaction also encourages them to adhere to their cessation plans more strictly.

The quantitative analysis provides insight into the participants' perceptions of human feedback, showing some positive correlations with engagement, accountability, and effectiveness. However, the correlations with users' smoking characteristics and the amount of weekly exercises were not statistically significant which gave us no further insights.

Based on the study's findings, integrating human feedback in eHealth applications for smoking cessation may enhance user support and commitment. Empathy and personalized feedback can make users feel understood, while interactive elements like regular check-ins and goal-setting sessions help maintain engagement. Providing constant encouragement and establishing accountability mechanisms can further sustain motivation and adherence to quitting plans.

Future research could explore the scalability of human feedback integration in eHealth applications, additional research into correlating quantitative data with the previously found themes could give further insights into them.

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A Appendix A

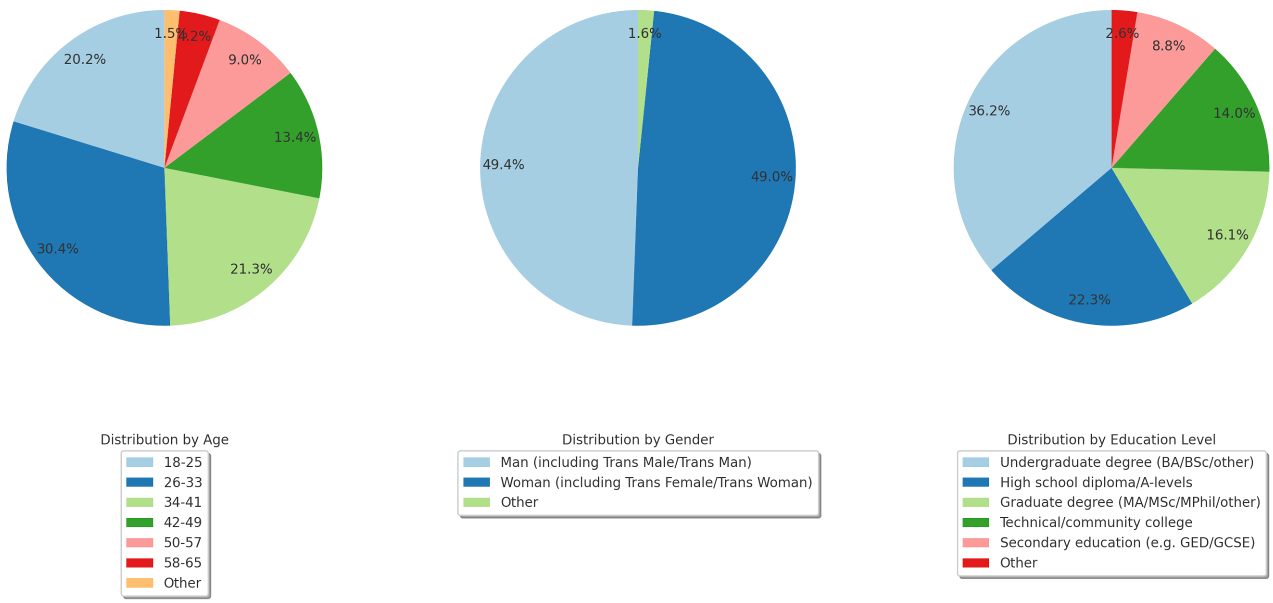

Figure 2: Characteristics of participants

B Appendix B

Code	Description
No difference	Participants perceived no significant difference/improvement after receiving the human feedback in comparison to the feedback from the virtual coach.
Real person	People prefer to communicate with real person.
Helpful	Participants describe the feedback as being useful or beneficial.
Support	People feel supported when receiving feedback from real people.
Personalized	Feedback was tailored specifically to the individual, enhancing relevance.
Emotional and understanding	Feedback was empathetic, showing emotional insight and understanding.
Repeats the Kai	Indicates feedback from the human coach was similar or identical to the virtual coach, Kai.
Different perspective/expert	The feedback offered new insights since it came from an expert viewpoint.
Engagement and interaction	People prefer the human feedback, because it is more engaging and more interactive.
Accountability	People feel accountable towards the real person.
Encouraging	The feedback was encouraging.
More motivating	People highlighted the motivational aspect of the feedback.
Neutral	Feedback that was neither positive nor negative; it was impartial.
Basic response	Feedback that was simple, basic, and not detailed.
Trust	People trust real people more than the virtual assistant and therefore prefer feedback from a real person.
Good/helpful advice	People find the advice from the experts as good/ helpful.
Provoke thinking	Feedback that challenged users to think deeply or reflect on their situation.
Kai is better	People preferred the virtual coach over a real person.
Reminding	Feedback that served as a reminder or a prompt.
Effectiveness and reliability	Participants think that the human feedback is more reliable and effective.
Guidance	Feedback that guided the users through the process, providing direction.
Valuable	Feedback that was particularly beneficial or of great value.
Rude	Feedback that was perceived as impolite or offensive.
Validating	Feedback validated or confirmed the user's feelings or actions.
Wrong suggestion	Feedback that was inappropriate or incorrect for the situation.

Table 15: Codes and their descriptions

C Appendix C

Code	Cohen's Kappa	Number of occurrences
no difference	0.8641	48
real person	0.8394	47
helpful	0.8390	40
support	0.8236	30
personalised	0.8873	37
emotional and understanding	0.8169	41
repeats Kai	0.8906	20
different perspective/expert	0.6564	22
engagement and interaction	0.7296	21
accountability	0.8104	12
encouraging	0.8906	17
more motivating	0.8670	16
neutral	0.7159	15
basic response	0.7278	12
trust	0.9546	12
good/helpful advice	0.7901	13
provoke thinking	0.9127	13
Kai is better	1.0000	7
reminding	1.0000	10
effectiveness and reliability	0.6072	9
guidance	0.8104	10
valuable	0.8870	4
rude	1.0000	2
validating	0.4972	2
wrong suggestion	0.6650	1

Table 16: Cohen's Kappa and Number of Occurrences for Each Code