How Ethical Perspectives Influence Smokers' Preferences for Time Allocation in Online Smoking Cessation Interventions

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Introduction

Smoking remains a major problem in society despite widely known facts about its harmful effects [1]. While technology can provide much support in smoking cessation interventions, it may lack the personal touch and emotional support many individuals need. One strategy to solve this is the integration of human coaching into online smoking cessation programs. However, human support is not as accessible or scalable as technological solutions and therefore must be strategically implemented. Understanding the perspectives of the users helps ensure that interventions are aligned with their needs.

Related work

Albers [2] suggests a set of ethical principles for offering human help in smoking cessation programs, based on Persad et al.'s [3] framework for offering scarce health resources and extending it with an additional principle. The original framework includes four principles: Treating people equally, Favoring the worst-off: prioritarianism, Maximizing total benefits: utilitarianism, and Promoting and rewarding social usefulness [3]. The additional principle is Respecting autonomy [2]. This study employs this principled framework, as it offers an ethical foundation for analysing the preference for the allocation of scarce human support in smoking cessation interventions.

Research Questions

How do smokers' ethical perspectives shape their preferences for time allocation mechanisms in online smoking cessation interventions?

Can large language models (LLMs) support qualitative analysis in practice?

Methodology

Manual Thematic Analysis

We used the six steps presented by Braun and Clarke [4]:

- Familiarizing with the dataset.
- Generating codes
- Searching themes
- Reviewing themes
- Defining
- Naming themes

Automatic Thematic Analysis

We tested two aspects:

1. whether an LLM could perform thematic analysis to identify themes within the user's responses
2. whether it could assign the found themes to these

We used a locally hosted version of the LLaMA model to have more control over processing. We selected the LLaMA 3 (8B) model because the LLaMA model has demonstrated the ability to capture language nuances [5], and variant 3 (8B) offers computational efficiency.

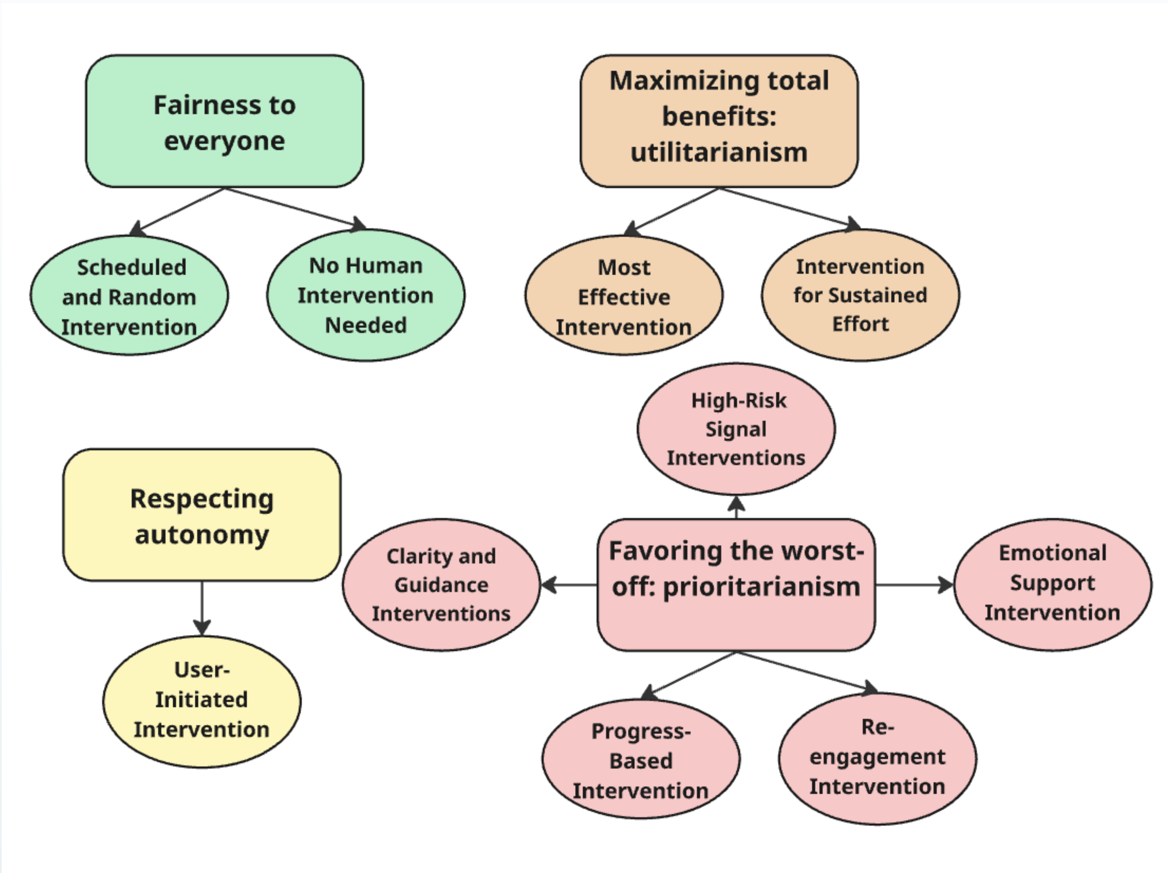
Comparison Between Open and Closed Responses

We compared the themes identified in the open-ended responses with the results of the closed question, in which participants allocated 100 points to 11 ethical principles. We wanted to see whether individuals tended to assign points to principles that aligned with the themes they had mentioned.

We used the Point-Biserial Correlation and p-values for this analysis. The point-biserial correlation is appropriate because it measures the strength of association between a binary variable (whether or not a participant mentioned a specific theme) and a continuous variable (the number of points they assigned to a corresponding principle) [6]. We calculated p-values to assess the statistical significance of each correlation [6].

According to the classification used by Dichoso and Cabauatan [7], the User-Initiated Interventions theme showed a reasonably good association and Scheduled and Random Interventions demonstrated marginal or acceptable correlations, both themes had statistically significant p-values, suggesting that the observed correlations are not the result of random variation. The remaining themes showed poor discrimination, indicating weak alignment between open and closed responses.

Results and Discussion



Themes and Corresponding Principles

Manual Theme	Automatic Theme
Scheduled and Random Interventions	Randomness and Equal Distribution
No Human Intervention Needed	N/A
User-Initiated Interventions	Request-based Intervention
Most Effective Intervention	Motivation and Engagement
Intervention for Sustained Effort	Motivation and Engagement
Emotional Support Interventions	Struggling Participants
Re-engagement Interventions	Low Motivation Scores
Progress-Based Interventions	Progress-based Intervention
Clarity and Guidance Interventions	Personalized Feedback
High-Risk Signal Interventions	Concerning Issues

Table 2: Correspondence Between Themes

The table shows the LLM themes alongside those from the manual analysis, revealing strong overlap.

We compared the list of themes assigned by the LLaMA model to those from our manual thematic analysis. Cohen's Kappa coefficient was used for this comparison. The result indicated 0.05 agreement, a "None" level, suggesting that the LLM did not reliably assign themes in alignment with the human analysis.

Conclusion

In conclusion, the ethical perspectives of smokers influence their preferences for time allocation mechanisms in online smoking cessation interventions, with multiple ways to implement each ethical principle. For fairness, users want interventions like Scheduled and Random Interventions or the No Human Intervention Needed option to provide fair support over time. For autonomy, User-Initiated Interventions were mentioned to allow users to control when they engage. Emotional Support Interventions, Re-engagement Interventions, Progress-Based Interventions, Clarity and Guidance Interventions, and High-Risk Signal Interventions reflect the ethical principle of favoring the worst off by prioritizing support for individuals at greater risk of not succeeding in the program. Preferences for maximizing total benefits were reflected in interventions such as the Most Effective Intervention and Intervention for Sustained Effort, which focus on achieving the greatest overall success.

Our results indicate that LLMs perform well at identifying themes and detecting patterns within the data, the thematic analysis done using the LLaMA model gave similar results to the manual thematic analysis performed by 2 coders. However, they are less accurate when it comes to assigning themes to individual messages. This suggests that LLMs can be a useful tool for theme discovery but require human support for thematic coding.

References

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