HapticMetric: A Smartphone Haptic Experience Computing System

Yixuan Li*
17825470707@163.com
The Future Laboratory, Tsinghua University
Beijing, China
School of Art and Design, Beijing Forestry University
Beijing, China

Rui Zhang*
gloriezhang777@gmail.com
The Future Laboratory, Tsinghua University
Beijing, China

Liwen He
helw24@mails.tsinghua.edu.cn
The Future Laboratory, Tsinghua University
Beijing, China

Yang Jiao†
jiaoyang7@tsinghua.edu.cn
The Future Laboratory, Tsinghua University
Beijing, China

Abstract

Smartphones have become ubiquitous electronic devices, and haptic feedback of smartphones plays a significant role for user experience. In recent years, there has been a growing demand for improved smartphone vibration feedback, resulting in increased design complexity due to the subjective and intricate nature of haptic perception. However, there is currently limited vibration computing available to support user experience designers in comprehensively assessing smartphone haptic feedback. This paper introduces HapticMetric, a smartphone haptic experience computing system. Firstly, 8 key physical factors associated with smartphone vibrations were identified and 24 pairs of adjectives were selected through literature review, and each pair of adjectives corresponds to one of these key factors. Secondly, through user experiment, exploratory and confirmatory factor analysis, we refined our system into 17 pairs of adjectives mapping with 5 factors. The results show that our system enhances users' and designers' understanding of the haptic experience by providing psychophysical metrics for haptic design. It offers valuable insights for future smartphone vibration waveform design and can be broadly applied to the design of other hardware, serving as an important measure in haptic design.

CCS Concepts

• **Human-centered computing → Human computer interaction (HCI)**; *Interaction devices*; *Haptic devices*;

Keywords

Haptic Experience, Smartphone, Physical Factors, Subjective Perception, Computing System

ACM Reference Format:
Yixuan Li, Rui Zhang, Liwen He, and Yang Jiao. 2024. HapticMetric: A Smartphone Haptic Experience Computing System. In *Proceedings of (CHCHI 2024).* ACM, New York, NY, USA, 10 pages. https://doi.org/XXXXXXX.XXXXXXX

1 Introduction

Smartphones are widely used electronic devices in the world [22], incorporate vibration as an integral component in their interactive systems, as evident in basic operations like "Keyboard Typing" and "Apps Long Press Editing", where haptics feedback is essential [29, 39]. With the development of haptic technology, mainstream smartphones are equipped with linear actuator along the X-axis to enhance haptic feedback. Some manufacturers have even introduced more powerful X-axis ultra-wide linear actuators to meet the growing demand for an upgraded haptic experience in smartphone usage. This increasing user demand has led designers to seek support from more realistic and diverse design tools [6].

Both industry and academia have been dedicated to improving the design of smartphone vibrations, focusing on functionality aspects such as vibration frequency [11, 34] and intensity perception [11, 39], to enhance user experience. As a result, designers expect to establish a connection between vibration design and user perception within the practical scenarios of smartphone usage.

However, there is currently a lack of 'Haptic Experience Computing Systems' designed for actual smartphone usage scenarios, such as keyboard typing and alarm setting. And the semantic attributes and evaluation criteria related to vibration perception in smartphone vibrations [12], user-side quantification and assessment of experiential aspects across diverse smartphone usage scenarios, require in-depth exploration and investigation. Consequently, smartphone vibration design calls for the development of a more standardized assessment system [19], and there are relatively few studies on the computation of haptic experience. We hope to quantify the user's subjective experience data to obtain a psychophysical

*Both authors contributed equally to this research.
†Corresponding Author.

CHCHI 2024, November 22–25, 2024, Shenzhen, China

ACM ISBN 978-1-4503-XXXX-X/18/06
https://doi.org/XXXXXXX.XXXXXXX

computation method that can guide the future design of haptic scenes.

To bridge this gap, in this paper we introduce HapticMetric, a smartphone haptic experience computing system. It is designed to provide a comprehensive computing framework for the smartphone vibration experience. Its primary goal is to empower haptic designers to conduct effective assessments and improve users' haptic experience. Firstly, we identified 8 key physical factors relevant to smartphone vibration scenarios. Based on previous literature, 24 adjective pairs were selected and each corresponds to one of these key factors. Furthermore, we refined the system through quantitative research, utilizing both exploratory and confirmatory factor analysis to delete inappropriate adjectives and revise classifications. This process ultimately resulted in HapticMetric, with 17 pairs of adjectives organized into 5 factors. Our study flow as shown in Fig.1.

This paper presents the following contributions. We present (1) HapticMetric: a haptic experience computing system based on smartphones. It encompasses 5 physical factors related to smartphone vibration scenarios and 17 pairs of adjectives, each mapped to one of physical factors. (2) Conduct user studies involving 144 trials on 12 real vibration feedback experience scenarios across 4 smartphones to collect relevant data, refine the system, and enhance its accuracy. (3) This system enhances users' and designers' understanding of the haptic experience by providing psychophysical metrics for haptic design, offering valuable guidance for haptic experience design.

2 Related Work

2.1 Research on Vibration Feedback of Smart Devices

Early smart device vibration technology primarily utilized eccentric motors. With advancements in the miniaturization of electromagnetic devices, smartphone vibrations are now generated by rotating an eccentric wheel within the vibration motor [10, 38], and its direction and amplitude are affected by the motor speed, installation position, and so on. These factors together determine the vibration comfort and can enable a more authentic and immersive user experience [13, 28, 29, 40]. Researchers emphasize the importance of vibration testing technology in optimizing engineering designs for better smartphone vibration experiences [10]. Wei et al. highlight the effectiveness of combining vibration amplitude and rhythm on mobile devices to maximize information recognition rates [36]. Ozer et al. based on vibration testing of a small-scale multistory laboratory model, monitored the displacement and acceleration responses of two different smartphone sensors [27]. Saket et al. investigate the potential for communication through modulated vibration motors in smartphones and decoding via accelerometers [29]. In the development of smartphone vibration function, Kim et al. noted that local haptic keystroke feedback enhances typing speed and reduces error rates on smartphones [20]. Yao et al. suggested that the perceived vibration intensity of smart devices depends on the difference between their weight and base frequency [39]. Sazenkot et al. enhanced navigation for the visually impaired using smartphone vibrations, varying pulse amounts, touch positions, and utilizing the built-in compass for directional guidance [2]. In summary, these studies show that optimizing vibration and adjusting functions can enhance user interaction and improve life convenience. However, in order to better analyze user subjected perceptions, we should also explore the relationship between objective physical vibration and subjective perception of the smartphone, and provide insights for further discussion and explanation from the perspective of psychophysics.

2.2 Psychophysics in Haptics

Haptics, a physiological sensation, is directly connected to psychology. The German physicist Fechner dedicated the study of the correlation between physiological and psychological aspects in psychophysics [8]. Psychophysics explores the interaction between physical stimuli and mental perceptions. Similarly, vibrations can convey individual subjective perceptions [17], influenced by the design of physical vibration, which stimulates varying subjective experiences. For example, Vicentini et al. prove that changes in frequency, duration, contact force will affect subjective perception [35]. Kording et al. argue that human perception is influenced by sensorimotor predictions, visual object information, and prior experience [21]. Moreover, there are also related studies focusing on changes in user emotions, Joung et al. prove that the emotion group of excited, happy, angry, and alarmed corresponds to high intensity and high temporal frequency [16]. Hwang et al. observed that as vibration frequency increases, participants tend to shift from negative evaluations to positive ones in their subjective perception [13]. In brief, researchers revise the user's subjective perception by improving mechanical [35] and information presentation effectiveness [32] of haptic interface, waveform interaction of combinations of amplitude, frequency, duration, etc.

2.3 The Relationship between Subjective Perception and Physical Vibration Factors

In order to better understand the user's subjective perception, relevant models, scales, and vocabulary have been used to compute haptic feelings in previous studies. The selection of descriptive adjectives often included physical characteristics [15, 26, 31], affective indicators [17, 41], and metaphorical expressions [30]. For example, Wu et al. used standard support vector machine (SVM) to classify the haptic adjectives, explored potential relationships and association effects between different adjectives [37]. Muramatsu et al. used semantic differential (SD) to gauge human subjects' mental perception of vibrotactile stimuli and built a cognitive model of haptic sensations [24]. Muender et al. proposed the Haptic Fidelity Framework to accurately describe the realism of haptic feedback [23]. In vocabulary selection, research aimed to identify emotional and sensory terms describing haptic experiences. Hwang et al. gathered adjectives representing subjective impressions of sinusoidal vibrations from mobile devices [13]. Guest et al. used a touch lexicon to delineate various aspects of haptic perception [12].

To aid user understanding of vibrations and enhance their ability to articulate subjective experiences, researchers conducted experiments using word descriptions related to various vibration modes to investigate the link between physical vibration and subjective perception. Fukuda et al. proved that fast and slow-tempo vibration patterns can induce users' sense of nervousness and calmness [9].

Figure 1: Study flow.

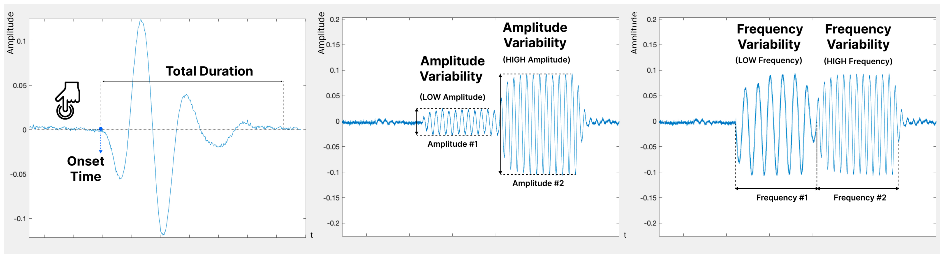

Figure 2: Performance comparison between different physical factors.

Obrist et al. explored how participants described haptic experiences involving two stimuli (16 Hz and 250 Hz) and introduced a vocabulary comprising 14 categories [26]. Shiraga et al. created user-defined vibration patterns and used adjectives to convey the corresponding sensory perceptions [31]. Hwang et al. measured user adaptation to 29 emotional expressions through vibrations and found that variations in sensitivity and emotional nuances along the X, Y, and Z axes create distinct vibration patterns [14]. It has been demonstrated that physical factors such as frequency and amplitude strongly influence users' subjective perception.

To sum up, while previous research has explored computing-based mapping of physical vibration factors to subjective perception, this work primarily focuses on evolutionary approaches that allow users to assess vibration patterns. The goal of our work is to develop a haptic experience computing system for smartphones that maps abstract physical vibration space into a user-friendly format. Unlike previous studies, we investigate the unique relationship between physical vibration factors and subjective perception in 12 common smartphone vibration scenarios, providing psychophysical metrics for haptic design.

3 Study Design

3.1 Identify the Physical Factors

In this stage, we sorted out 8 physical factors of smartphone vibration according to the characteristics of different scenarios of smartphones. We categorize the key physical factors of smartphone vibration waveforms as shown in Fig.2. The following 6 physical factors provide a clear indication of the fundamental properties of vibration. These factors include *"Onset Time"* representing the response time of vibration signals; *"Total Duration"* representing the temporal extent of the vibration signal; *"Overall Amplitude"* and *"Overall Frequency"* represents the overall perception of amplitude and frequency in a vibration signal. Moreover, grounded in the dual factors of vibration amplitude and frequency, we further dissect user perceptions of smartphone vibrations into *"Amplitude Variability"* which refer to the degree of amplitude fluctuation within the vibration signal, and *"Frequency Variability"* which assesses the extent of frequency fluctuation within the signal. *"Amplitude Characteristics"* and *"Frequency Characteristics"* are not included in these six factors. Instead, they are mainly formed by the combination of several vibration features, typically refer to the specific attributes of amplitude and frequency within a given vibration signal. These attributes serve to describe the features related to the intensity, magnitude of the vibration signal, encompassing aspects such as mean amplitude, peak amplitude, frequency range. We believe that these *"Amplitude Characteristics"* and *"Frequency Characteristics"* can demonstrate the user's experience as much as possible, and increase the designer's design possibilities.

3.2 Select Sensory Adjectives

We have chosen 6 adjectives corresponding to the preceding 6 physical factors to vividly describe the psychological perception elicited by smartphone vibrations, as shown in Fig. 3.

To address *"Amplitude Characteristics"* and *"Frequency Characteristics"*, our goal is to heighten user perception and expand the design possibilities for waveform creation. We applied the Semantic Differential Method to understand users' perceptions and emotional assessments of various vibration signals. To address *"Amplitude Characteristics"* and *"Frequency Characteristics"*, our goal is to heighten user perception and expand the design possibilities for waveform creation. We applied the Semantic Differential Method to understand users' perceptions and emotional assessments of various vibration signals. Drawing on Gest et al.'s research, which indicated that evaluative words often included additional descriptions of sensory and emotional aspects of touch and ranked lower in evaluative nature, we excluded such adjectives from further research. Additionally, terms with strong emotional inclinations were excluded to prevent potential disruptions in user descriptions [12]. Through an extensive literature review and focused group discussions, we explored the semantic relationships between sensory adjectives and conducted a preliminary vocabulary screening.

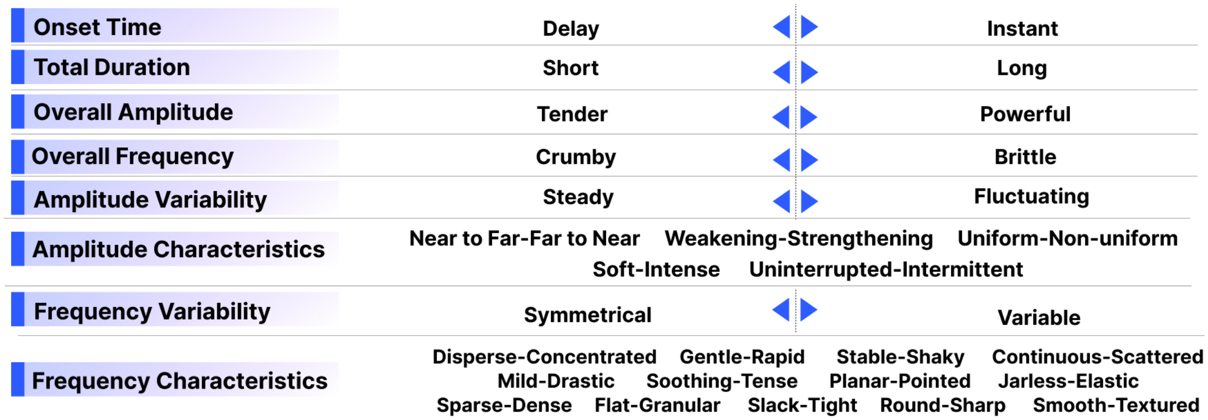

Figure 3: The mapping relationship between physical factors and adjective pairs.

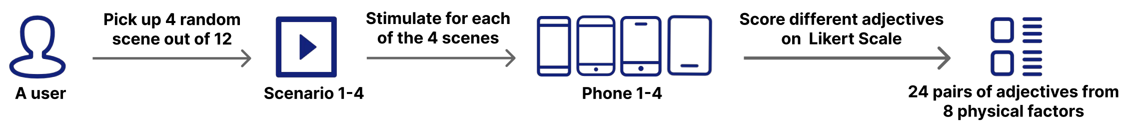

Figure 4: User experiment procedure.

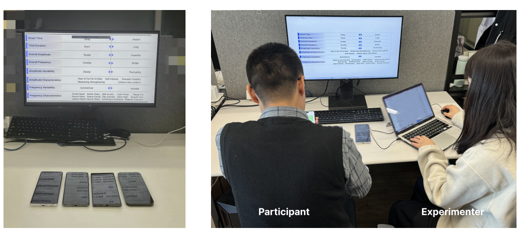

Figure 5: Experimental environment.

Based on a comprehensive literature review, we selected adjectives that better align with the haptic feedback from smartphones: *slack, sharp, soothing, tight, intense* [12], *elastic* [5, 12], *dense* [5, 12, 13], *sparse* [13], *steady* [31], *gentle*, *soft* [12, 13, 26], *smooth* [12, 13, 31]. Additionally, we introduced metaphorical adjectives relevant to the tactile feedback of mobile devices, such as *Pointed* and *Brittle* [12]. To enhance user understanding and ensure accurate characterization, we also selected antonyms for these adjectives [31]. Ultimately, we have selected 24 pairs of adjectives, such as (e.g., *Soft-Intense*, *Mild-Drastic*). Most of these are related to sensory experiences, forming a strong connection with the physical factors of vibration and closely linking with haptic perception. These words are used to express users' real perception and will be confirmed during the data analysis, as detailed in Fig. 3.

3.3 Smartphones and Scenarios Selection

To conduct a thorough evaluation, we selected four popular smartphones from best-selling brands in 2023. The selected devices and their vibration motors were as follows: iPhone 14 Pro Max (Apple Taptic Engine), Samsung Galaxy S23 Ultra (AAC Technologies SLA 0620), OnePlus 11 (AAC Technologies CSA 0916), and Xiaomi 13 Pro (AAC Technologies ESA 1016). In the experiment, we set each smartphone's operating system to its highest haptic feedback level to optimize the user's vibration perception experience.

Smartphone vibration scenarios can be categorized into two types of triggered behaviors: pressing and sliding. In the pressing category, actions are further divided based on the duration of finger contact into short press (e.g., "Keyboard Typing") and long press (e.g., "Album Long Press Editing"). For the sliding category, actions are classified into four types according to the sliding direction: downward, upward (e.g., "Contact Alphabet Index"), leftward, and rightward (e.g., "Horizontal Switch Setting"). To ensure the experimental scenarios represent a variety of vibration-triggering behaviors, we selected 12 high-frequency scenarios. These include "Keyboard Typing, Alarm Setting, Contact Alphabet Index, Camera Zoom Adjustment, Camera Shooting, Camera Continuous Shooting, Album Long Press Editing, Apps Long Press Editing, Horizontal Switch Setting, Swiping Up to Access Recent Tasks, Wired Charging, Long Press to Power Off".

4 Method

4.1 Participants

To collect users' perceptions of various adjective pairs, we conducted a study with 36 participants, including 15 females and 21 males, aged between 19 and 55 (M = 28.06, SD = 6.88). Each participant took part in four randomly assigned scenarios. In total, 144 trial sessions were conducted across the 12 scenarios, with 12 participants assigned to each scenario. Each session lasted 20 minutes per participant, amounting to a total experiment time of

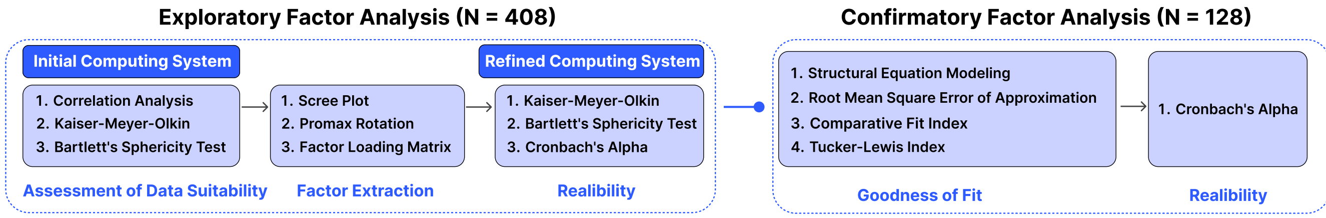

Figure 6: Data analysis procedure.

approximately 48 hours. All participants were right-handed and reported normal tactile perception. Monetary compensation was provided to participants in recognition of the time spent in the study. The study procedures were approved by the Research Ethics Board.

4.2 Procedure

The experimental procedure is illustrated in Fig. 4, while the environment setup is shown in Fig. 5. Following an introduction to the experiment's details and tasks by the experimenter, each participant completed tests across four distinct vibration scenarios. To minimize external noise and contextual distractions, all experiments were conducted in a quiet, enclosed indoor setting. For example, the participant's experience process in one scenario is as follows:

- Randomly select one of the 12 scenarios.
- Use either a single-handed or double-handed grip, based on personal habit, to perceive and compare the haptic feedback of four smartphones.
- Evaluate each phone by rating 24 adjective pairs on a 7-point Likert scale.

On this scale, a rating of "1" indicated that the haptic perception was highly aligned with the first word, while a rating of "7" signified a strong alignment with the second word.

4.3 Data Cleaning and Analysis

In each scenario, data from 4 different devices were collected, resulting in a total of 576 data sets, calculated as 12 scenarios × 12 trials × 4 smartphones.

To enhance data quality for analysis, the Z-score method was applied to identify and remove outliers, with data points exceeding 2 standard deviations considered as outliers. Data cleaning was performed separately for the samples within the 12 scenarios, resulting in the removal of 40 samples. A final dataset of 536 samples was used for analysis.

The cleaned data was then divided into two subsets: one consisting of 408 samples for Exploratory Factor Analysis (EFA) and the other comprising 128 samples for Confirmatory Factor Analysis (CFA). These analyses played a key role in refining the computing system. The process is illustrated in Fig. 6.

5 Exploratory Factor Analysis

Exploratory factor analysis aims to understand the underlying structure and characteristics of data by grouping similar observed variables into the same factors to generate the best structure.

In our study, adjectives were treated as observed variables, and we explored the proposed system structure and revised it.

5.1 Assessment of Data Suitability

To determine whether the data is suitable, we analyzed our data based on three different criteria. Firstly, we used a correlation matrix to assess the strength of relationships among the adjectives. Upon validation, there were 250 correlation coefficients greater than 0.3 in Fig.7 (dim1-24 are the 24 pairs of adjectives from Fig. 3), the correlation analysis heatmap indicates that the data is correlated and suitable for factor analysis. Generally, for a comprehensive factor analysis, the correlation matrix must contain correlation coefficients >0.3.

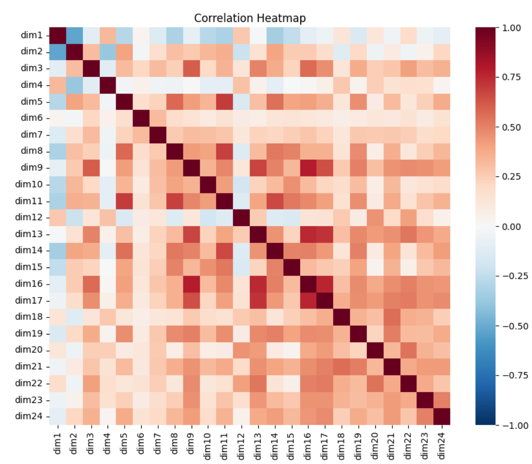

Figure 7: Correlation analysis heatmap. The X-axis is dimension1-dimension24 from left to right, the Y-axis is dimension24-dimension1 from bottom to top.

Next, we performed the Kaiser-Meyer-Olkin (KMO) test to calculate the variance proportions between the adjectives. Our test results (KMO=0.88) tends to 1 [18], indicated adequate factorability. The KMO value ranges from 0 to 1, with values closer to 1 being better. KMO values less than 0.6 suggest that the data is not suitable for factor analysis.

Lastly, we applied Bartlett's test of Sphericity [33]. The result ($\mathcal{X}^2$ = 208.5023, p <0.05) indicates the adjectives are sufficiently correlated. It is used to test the hypothesis of non-orthogonal variables, i.e., substantial correlations.

5.2 Factor Extraction

We determined a Scree plot to explore the number of ideal number of underlying factors. Considering that the factors *"Onset Time"* and *"Total Duration"* were previously represented by only one adjective pair in the system, and they exhibit relatively strong independence from the categories of adjectives related to frequency, amplitude, etc., we have temporarily excluded these two factors from the factor analysis. Our analysis is focused on the remaining 22 pairs of adjectives. As shown in Fig. 8, the plot starts to level off at around the 3rd component and become more stable around the 5th component, indicating the presence of 3-5 factors in the 22 adjectives.

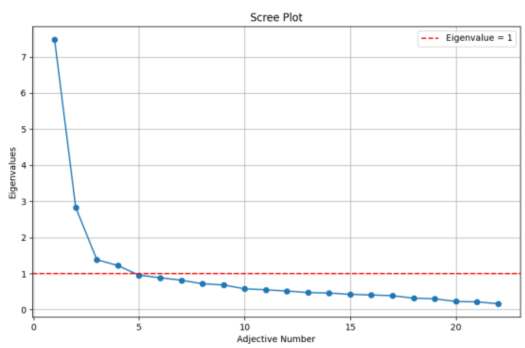

Figure 8: Scree plot with decreasing eigenvalues with respect to the number of possible factors. A steep drop at the 3rd component and a more subtle drop at the 5th component indicates that there could be between 3-5 underlying factors in the 22 adjectives.

Next, based on the continuity of values obtained from the 7-point Likert Scale and the characteristics of data samples comprising multiple variables, we determined the "Principal Axis Factoring" method for factor extraction. When selecting the factor rotation type, due to the high intercorrelations among the indicators (with 50% of the intercorrelations exceeding 0.3), we chose oblique rotation and achieved the best results with "promax" rotation. Throughout this process, we iterated and compared models, including 3-factor, 4-factor, and 5-factor models. We found that the 3-factor model for the 22 adjectives exhibited the best data fit and conceptual interpretability.

5.3 System Refinement and Reliability

After performing factor analysis, we refined our adjectives based on two criteria. Firstly, we included an adjective only if its loading was above the recommended threshold of 0.50. This ensures that the extracted adjectives has a significant association with the underlying factor [25]. Secondly, the adjective did not load significantly on other factors. This step affirms that variances in adjectives are uniquely associated to their respective factors only and not to other factors. As a result, the following 7 pairs of adjectives were removed: *Near to Far—Far to Near*, *Weakening—Strengthening*, *Disperse—Concentrated*, *Jarless—Elastic*, *Sparse—Dense*, *Round—Sharp*, *Smooth—Textured*. Consequently, 15 pairs of adjectives were retained. The extracted adjectives and their correlations are shown in Table 1.

Table 1: 15 adjectives loading score on their respective factors

Adjectives	Loading Score		
	Factor1	Factor2	Factor3
Tender—Powerful	0.6891		
Soft-Intense	0.774		
Gentle-Rapid	0.8419		
Mild-Drastic	0.8707		
Soothing—Tense	0.7517		
Slack-Tight	0.6822		
Crumby—Brittle		0.3971	
Planar-Pointed		0.7657	
Flat-Granular		0.5058	
Steady—Fluctuating			0.7022
Uniform—Non-uniform			0.7871
Uninterrupted-Intermittent			0.5274
Symmetrical-Variable			0.8622
Stable-Shaky			0.6377
Continuous-Scattered			0.7134

Finally, we conducted a second analysis on the retained 15 pairs of adjectives. The Kaiser-Meyer-Olkin (KMO) value was 0.83, with majority adjectives having values KMO $\geq$ 0.7, indicating good sampling adequacy. Bartlett's test of sphericity ($\mathcal{X}^2$ = 43.83, p <0.05) also confirmed the factorability of the 15 words.

To assess the internal consistency of the indicators, we calculated Cronbach's α, with an overall α exceeding 0.6 and most sub-scales exceeding 0.7 indicating sufficient reliability. the test results (Overall α = 0.88, with most sub-scales α >0.8) demonstrate the system is sufficiently reliable, and consistent results are expected when repeated under similar conditions.

6 Confirmatory Factor Analysis

We used the validation set (N=128) to conduct Confirmatory Factor Analysis (CFA) to validate the fit of the revised model obtained from EFA. CFA is employed to assess the consistency of the hypothesized model derived from EFA with new sample data [7].

In the confirmatory analysis, we used Structural Equation Modeling (SEM) in AMOS to calculate the validation set's data and determine whether the observed model fit well. The final Equation as shown in Fig.9. Additionally, we used Cronbach's α to assess the internal consistency.

6.1 Goodness of Fit

To assess the goodness of fit of the model, we calculated the Root Mean Square Error of Approximation (RMSEA), which measures the extent to which the model reproduces the covariance among items. A RMSEA value of $\leq$ 0.05 indicates a close fit, $0.05 \leq RMSEA < 0.1$

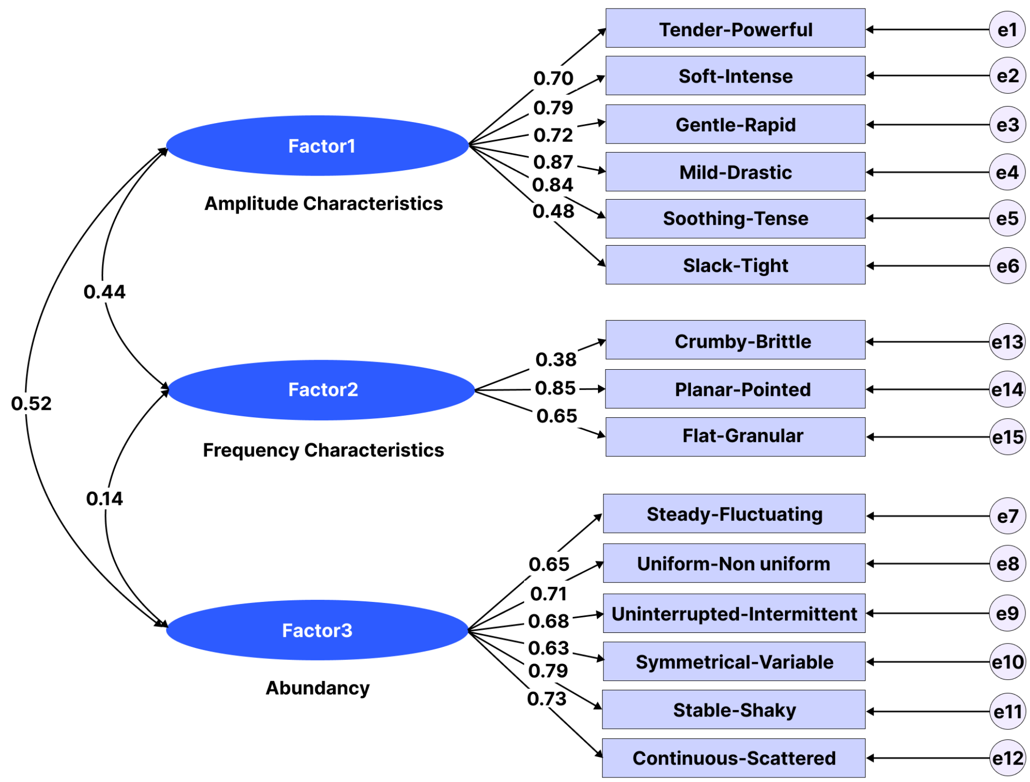

Figure 9: Structural equation modeling with loading score.

suggests a reasonable fit, and > 0.1 indicates a poor fit [4]. Our model's RMSEA 0.078 indicates a reasonable fit.

Additionally, we computed the Comparative Fit Index (CFI) and the Tucker-Lewis Index (TLI). The obtained results for CFI and TLI were 0.924 and 0.905, respectively, both exceeding the recommended threshold of 0.90, indicating good model performance [4].

By analyzing the factor loadings of different adjective pairs in the factor loadings matrix, we merged the original *"Overall Amplitude"* and *"Amplitude Characteristics"* into *"Amplitude Characteristics"*, combined *"Overall Frequency"* and *"Frequency Characteristics"* into *"Frequency Characteristics"*, and unified *"Amplitude and Frequency Variability"* into *"Abundancy"*. This consolidation resulted in three factors related to magnitude, frequency, and variation. After merging the 2 time-related factors *("Onset Timing" and "Total Duration")*, we got the revised 5-factor system.

6.2 Reliability

To ensure the 5-factor model's reliability, we calculated Cronbach's α using the validation set (N=128). The results showed good internal consistency with an overall α of 0.85, with most sub-scales having α>0.8 and all sub-scales having α>0.6. The final HapticMetric system as shown in Fig. 10.

7 Discussion

7.1 Design Implications and Research Opportunities

Wide Range of Applicability. The HapticMetric is a smartphone Haptic Experience Computing System based on 12 high-frequency scenarios, designed to bridge the gap between the physical factors of vibrations and subjective metrics. This approach to computing haptic interaction experiences can be applied to various scenarios, replicating and extending its use to other haptic interactions, feedback, and experiences. For example, further research on haptic experience in the fields of message notification, entertainment applications, mobile games, etc. Enhance the immersion, pleasure, and goal-matching of more scenes by enhancing the tactile experience. In addition, for users who require special attention to haptic feedback, such as the visually or hearing-impaired, the model can be used to improve mobile phone assistive technology and help disabled people interact with mobile phones more easily. [2], [3].

Variability in User Preferences and Thresholds. Our research also explored the interaction of user preferences. During the experiment, we found that different users have different preferences for vibration perception. Our research also delved into user preferences, revealing variations in vibration perception among different users. For instance, when considering the adjective index *Tender*

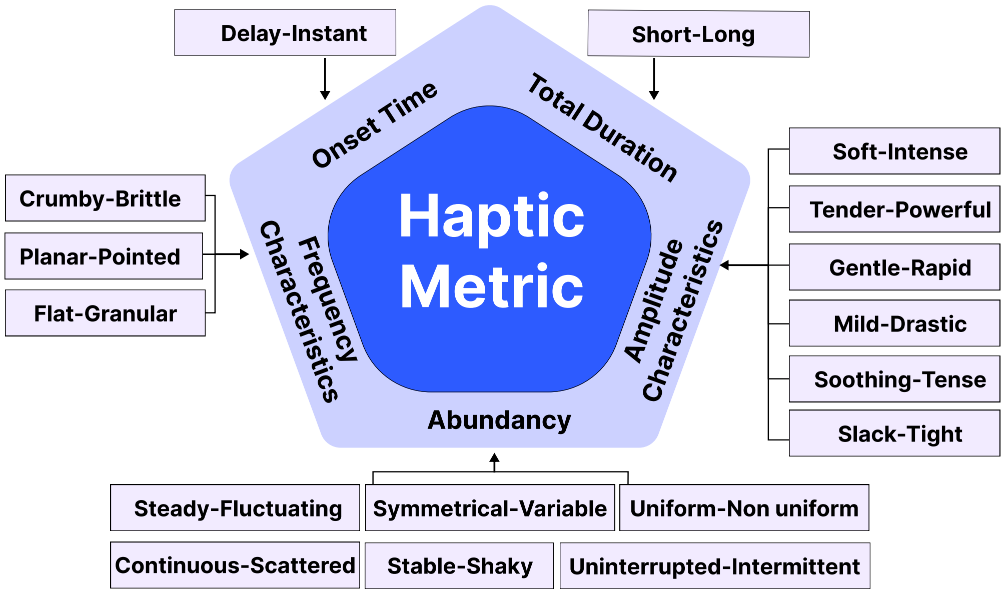

Figure 10: Haptic experience computing system: HapticMetric.

- *Powerful*, the majority of users favored a slightly gentler vibration, but some gamers showed a preference for stronger vibrations. Considering the increasing significance of user experience in the future, there is a likelihood that various personalized modes for mobile phone vibration design will be developed and implemented. Once users have rated their preferred phone vibration effect using the HapticMetric description, the phone can then customize the vibration feedback to align with their individual preferences. In these scenarios, HapticMetric holds the potential to revolutionize the field of haptic design, thereby enhancing user experiences in diverse contexts.

7.2 Differences with Other Vibration Perception Models and Systems

There are several distinctions between our system and other vibration perception systems. Unlike the model proposed by Marianna Obrist et al., which directly presents 14 categories of descriptive haptic perceptions without dividing them into dimensions [26], our system involved a thorough analysis of vocabulary to categorize adjectives and establish a connection with physical factors. Moreover, comparing with the touch lexicon established by Guest et al., which consists of 26 "sensory" attributes (e.g., *Bumpiness*) and 14 "emotional" attributes (e.g., *Pleasurable*), it is based on sensory and perceptual aspects. In contrast, our HapticMetric does not delve into emotional aspects but rather relies on objective descriptive adjectives to establish links to physical perceptions [12].

Besides, Ahmed et al. optimized the HX standard's 5-factor model to propose a more general 4-factor model, including attributes like *Realism, Harmony, Involvement* and *Expressivity*. However, the results obtained can not be directly related to the physical factors of vibrations [1]. In contrast, our model's five factors *("Onset Time, Overall Duration, Amplitude Characteristics, Frequency Characteristics, Abundancy")* not only help users describe haptic experiences but also provide direct guidance for vibrations design to designers.

8 Limitation and Future Work

In the course of our research, we observed that the overall haptic experience is not only related to waveform design but also influenced by hardware such as the motor (performance parameters, size, placement) and the phone itself (material, size). For example, apple uses the Taptic Engine, while Xiaomi uses the AAC Technologies ESA 1016 motor, and the two mobile devices differ in terms of size, weight, screen curvature, and material composition, all of which can affect user perception and judgment of vibrations. For future work we plan to conduct experiments controlling for these variables to eliminate their influence.

Another limitation in our research is although we have identified the mapping relationship between objective vibration physical factors and subjective adjectives, and validated users' ideal values for each dimension. However, we have not yet determined the specific duration, magnitude, frequency, and other physical parameter ranges corresponding to the numerical values of each adjective. Further measurements work can be undertaken for vibration waveforms to construct a complete "Measure physical vibration factors – Map subjective adjectives – Derive physical parameter ranges" haptic design guideline. This will assist haptic designers to revising vibration effects and enhancing user experiences.

HapticMetric also shows great potential for personalization. Our study highlights variability in user preferences, but it does not fully explore customizable feedback settings [42]. Given the diversity in user expectations, an personalized version or toolkit of HapticMetric could be a valuable direction for future research, enabling users to fine-tune haptic feedback according to their preferences. Furthermore, the scenarios in this study primarily focused on smartphone system vibrations and did not include an analysis of vibration scenarios related to message notifications (such as messages or phone calls) or gaming and music-related vibrations. To expand our system, future research could consider combining auditory and visual information to provide richer descriptions of haptic feedback, allowing for a more comprehensive understanding of user experiences.

HapticMetric is a comprehensive pipeline for computing subjective data related to haptic experiences. This system has the potential to be utilized in designing metrics for a wide range of haptic interactions in the future. For instance, it could enhance VR and smartwatch experiences by providing refined haptic experience metrics, allowing designers to create more nuanced and realistic haptic feedback. By leveraging this pipeline, researchers and developers can create more immersive and effective haptic interfaces across various applications.

9 Conclusion

This paper introduces HapticMetric, a Haptic Experience Computing System designed for smartphones. We conducted 144 user trials, testing 4 different smartphones across 12 common scenarios. The analysis of user experimental data in these scenarios resulted in a reduction from the initial 24 pairs of adjectives to 17 pairs, each mapping to one of the 5 specific physical factors. This process led to the development and significance of the HapticMetric system, which extends to both theoretical and practical realms within the field of haptic research.

Acknowledgments

We express our heartfelt thanks to Yuxin Chen, Ziyue Qiu, Jiawen Zhang, and Yijie Pu for their contributions to this project. We are also grateful to all the participants for dedicating their time and effort. In addition, we appreciate the anonymous reviewers for their valuable and constructive feedback. This research was funded by the Foundation of the Ministry of Education of China (23YJCZH092) and supported by a research grant from Xiaomi Inc.

References

[1] Ahmed Anwar, Tianzheng Shi, and Oliver Schneider. 2023. Factors of Haptic Experience across Multiple Haptic Modalities. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. 1–12.

[2] Shiri Azenkot, Richard E Ladner, and Jacob O Wobbrock. 2011. Smartphone haptic feedback for nonvisual wayfinding. In *The proceedings of the 13th international ACM SIGACCESS conference on Computers and accessibility*. 281–282.

[3] Shiri Azenkot, Kyle Rector, Richard Ladner, and Jacob Wobbrock. 2012. PassChords: secure multi-touch authentication for blind people. In *Proceedings of the 14th international ACM SIGACCESS conference on Computers and accessibility*. 159–166.

[4] Peter M Bentler and Douglas G Bonett. 1980. Significance tests and goodness of fit in the analysis of covariance structures. *Psychological bulletin* 88, 3 (1980), 588.

[5] Nalini Bhushan, A Ravishankar Rao, and Gerald L Lohse. 1997. The texture lexicon: Understanding the categorization of visual texture terms and their relationship to texture images. *Cognitive science* 21, 2 (1997), 219–246.

[6] Lorna M Brown and Topi Kaaresoja. 2006. Feel who's talking: using tactons for mobile phone alerts. In *CHI'06 extended abstracts on Human factors in computing systems*. 604–609.

[7] Timothy A Brown. 2015. *Confirmatory factor analysis for applied research*. Guilford publications.

[8] Gustav Theodor Fechner. 1948. Elements of psychophysics, 1860. (1948).

[9] Ryusei Fukuda, Shinji Miyake, and Daiji Kobayashi. 2024. Evaluating Smartphone Vibration Patterns and Evoked. In *Proceedings of the Workshop on Computation: Theory and Practice (WCTP 2023)*, Vol. 20. Springer Nature, 69.

[10] Ganggang Gao et al. 2023. Vibration Detection for Mobile Phone Based on Digital Image Correlation Method. *The Frontiers of Society, Science and Technology* 5, 5 (2023).

[11] J Giacomin, MS Shayaa, E Dormegnie, and L Richard. 2004. Frequency weighting for the evaluation of steering wheel rotational vibration. *International journal of industrial ergonomics* 33, 6 (2004), 527–541.

[12] Steve Guest, Jean Marc Dessirier, Anahit Mehrabyan, Francis McGlone, Greg Essick, George Gescheider, Anne Fontana, Rui Xiong, Rochelle Ackerley, and Kevin Blot. 2011. The development and validation of sensory and emotional scales of touch perception. *Attention, Perception, & Psychophysics* 73 (2011), 531–550.

[13] Inwook Hwang and Seungmoon Choi. 2010. Perceptual space and adjective rating of sinusoidal vibrations perceived via mobile device. In *2010 IEEE Haptics Symposium*. IEEE, 1–8.

[14] Jihong Hwang and Wonil Hwang. 2011. Vibration perception and excitatory direction for haptic devices. *Journal of Intelligent Manufacturing* 22 (2011), 17–27.

[15] Fumiya Ito and Kenjiro Takemura. 2021. A model for estimating tactile sensation by machine learning based on vibration information obtained while touching an object. *Sensors* 21, 23 (2021), 7772.

[16] Hae Youn Joung and Ellen Yi-Luen Do. 2011. Tactile hand gesture recognition through haptic feedback for affective online communication. In *Universal Access in Human-Computer Interaction. Users Diversity: 6th International Conference, UAHCI 2011, Held as Part of HCI International 2011, Orlando, FL, USA, July 9-14, 2011, Proceedings, Part II 6*. Springer, 555–563.

[17] Yulan Ju, Dingding Zheng, Danny Hynds, George Chernyshov, Kai Kunze, and Kouta Minamizawa. 2021. Haptic empathy: Conveying emotional meaning through vibrotactile feedback. In *Extended Abstracts of the 2021 CHI Conference on Human Factors in Computing Systems*. 1–7.

[18] Henry F Kaiser. 1970. A second generation little jiffy. (1970).

[19] Erin Kim and Oliver Schneider. 2020. Defining haptic experience: Foundations for understanding, communicating, and evaluating HX. In *Proceedings of the 2020 CHI conference on human factors in computing systems*. 1–13.

[20] Jin Ryong Kim and Hong Z Tan. 2014. A study of touch typing performance with keyclick feedback. In *2014 IEEE Haptics Symposium (HAPTICS)*. IEEE, 227–233.

[21] Konrad P Kording, Shih-pi Ku, and Daniel M Wolpert. 2004. Bayesian integration in force estimation. *Journal of neurophysiology* 92, 5 (2004), 3161–3165.

[22] Heow Pueh Lee and Siak Piang Lim. 2014. Comparative studies of perceived vibration strength for commercial mobile phones. *Applied ergonomics* 45, 3 (2014), 807–810.

[23] Thomas Muender, Michael Bonfert, Anke Verena Reinschluessel, Rainer Malaka, and Tanja Döring. 2022. Haptic fidelity framework: Defining the factors of realistic haptic feedback for virtual reality. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*. 1–17.

[24] Yuichi Muramatsu and Mihoko Niitsuma. 2013. Correspondence relationships between vibrotactile stimuli and tactile sensations determined by semantic differential. In *2013 IEEE RO-MAN*. IEEE, 668–673.

[25] Richard G Netemeyer, William O Bearden, and Subhash Sharma. 2003. *Scaling procedures: Issues and applications*. sage publications.

[26] Marianna Obrist, Sue Ann Seah, and Sriram Subramanian. 2013. Talking about tactile experiences. In *Proceedings of the SIGCHI conference on human factors in computing systems*. 1659–1668.

[27] Ekin Ozer, Dongming Feng, and Maria Q Feng. 2017. Hybrid motion sensing and experimental modal analysis using collocated smartphone camera and accelerometers. *Measurement Science and Technology* 28, 10 (2017), 105903.

[28] Jonghyun Ryu, Chil-Woo Lee, and Seungmoon Choi. 2010. Improving vibrotactile pattern identification for mobile devices using perceptually transparent rendering. In *Proceedings of the 12th international conference on Human computer interaction with mobile devices and services*. 257–260.

[29] Bahador Saket, Chrisnawan Prasojo, Yongfeng Huang, and Shengdong Zhao. 2013. Designing an effective vibration-based notification interface for mobile phones. In *Proceedings of the 2013 conference on Computer supported cooperative work*. 149–1504.

[30] Hasti Seifi, Kailun Zhang, and Karon E MacLean. 2015. VibViz: Organizing, visualizing and navigating vibration libraries. In *2015 IEEE World Haptics Conference (WHC)*. IEEE, 254–259.

[31] Shota Shiraga, Yuichiro Kinoshita, and Kentaro Go. 2016. Designing smartphone feedback based on vibration impression. In *Proceedings of the 2016 CHI Conference Extended Abstracts on Human Factors in Computing Systems*. 3190–3196.

[32] Hong Tan, Adrian Lim, and Ryan Traylor. 2000. A psychophysical study of sensory saltation with an open response paradigm. In *ASME International Mechanical Engineering Congress and Exposition*, Vol. 26652. American Society of Mechanical Engineers, 1109–1115.

[33] Sigmund Tobias and James E Carlson. 1969. Brief report: Bartlett's test of sphericity and chance findings in factor analysis. *Multivariate behavioral research* 4, 3 (1969), 375–377.

[34] M Tommerdahl, KD Hester, ER Felix, M Hollins, OV Favorov, PM Quibrera, and BL Whitsel. 2005. Human vibrotactile frequency discriminative capacity after adaptation to 25 Hz or 200 Hz stimulation. *Brain research* 1057, 1-2 (2005), 1–9.

[35] Marco Vicentini and Debora Botturi. 2010. Perceptual issues improve haptic systems performance. *Advances in haptics* (2010), 415–438.

[36] Side Wei, Gang Ren, and Eamonn O'Neill. 2014. Haptic and audio displays for augmented reality tourism applications. In *2014 IEEE Haptics Symposium (HAPTICS)*. IEEE, 485–488.

[37] Hancheng Wu, Xiang Liu, Senlin Fang, Zhengkun Yi, and Xinyu Wu. 2020. Leveraging multi-label correlation for tactile adjective recognition. In *2020 3rd International Conference on Robotics, Control and Automation Engineering (RCAE)*. IEEE, 122–126.

[38] Tae-Heon Yang, Dongbum Pyo, Sang-Youn Kim, and Dong-Soo Kwon. 2016. Development and evaluation of an impact vibration actuator using an unstable mass for mobile devices. *International Journal of Control, Automation and Systems* 14, 3 (2016), 827–834.

[39] Hsin-Yun Yao, Danny Grant, and Manuel Cruz. 2009. Perceived vibration strength in mobile devices: The effect of weight and frequency. *IEEE Transactions on Haptics* 3, 1 (2009), 56–62.

[40] Koji Yatani and Khai Nhut Truong. 2009. SemFeel: a user interface with semantic tactile feedback for mobile touch-screen devices. In *Proceedings of the 22nd annual ACM symposium on User interface software and technology*. 111–120.

[41] Yongjae Yoo, Taekbeom Yoo, Jihyun Kong, and Seungmoon Choi. 2015. Emotional responses of tactile icons: Effects of amplitude, frequency, duration, and envelope. In *2015 ieee world haptics conference (whc)*. IEEE, 235–240.

[42] Rui Zhang, Yixuan Li, Zihuang Wu, Yong Zhang, Jie Zhao, and Yang Jiao. 2024. SemanticTap: A Haptic Toolkit for Vibration Semantic Design of Smartphone. In *Proceedings of the 26th International Conference on Multimodal Interaction*. 264–273.