Using the Price Sensitivity Meter to Measure the Value of Transformative Robot Sound

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***Abstract*— Transformative robot sound can improve perceptions of robots, but its implementation will likely require more hardware and cost. Does the addition of transformative sound yield an increase in value to offset this cost? Using the van Westendorp Price Sensitivity Meter, a questionnaire from marketing research, $n = 97$ participants measured acceptable price points for a robot with (and without) transformative sound. Results showed similar perceptual improvements as past studies, as well as a significant increase in perceived value, when transformative sound was included. These increases in social and value perceptions of robots confirm the utility of adding transformative sound to robots. This work benefits the broader human-robot interaction research community by sharing more ways to understand and validate the incorporation of transformative robot sound and other robot features.**

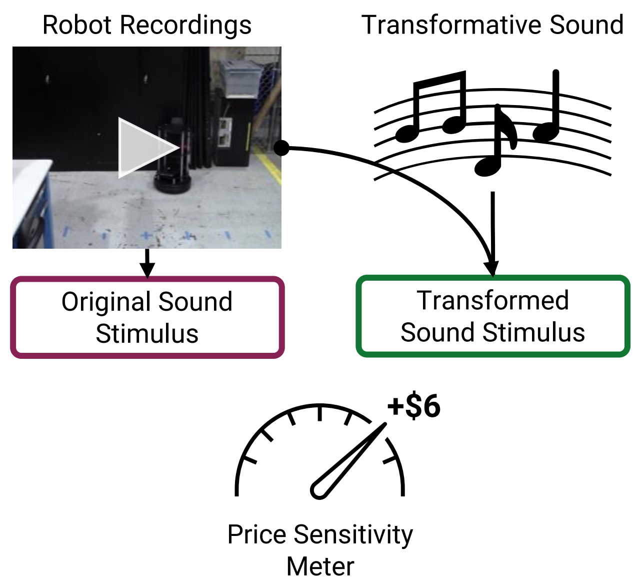

Fig. 1: An overview of the study manipulation and the primary result: a significant increase in perceived value due to transformative sound.

I. Introduction

Transformative robot sound—intentionally added non-linguistic sound that complements a robot's normal sound profile—is universal for robots that appear in popular media, yet is often uncommon for robots in the real world. Our past work, which first introduced transformative sound, has shown that transformative sound makes robots seem more energetic, happier, warmer, and more competent [1]. However, adding transformative sound to robots may incur additional production costs, as many robots currently lack audio hardware [2]. Using the van Westendorp Price Sensitivity Meter (PSM), a widely used technique in market research [3], we aimed to answer the question: *do the perceptual benefits of adding transformative robot sound translate to increased perceived value for users?*

Value is a complex construct that encompasses aspects such as practical and perceptual features and personal trade-offs. Past work in human-robot interaction (HRI) has attempted to measure value [4]–[6], but to the authors' best knowledge, HRI lacks an accepted measurement instrument for *perceived value* [7]. Related work in human-computer interaction (HCI) has previously proposed using the PSM as a tool for value-based software engineering [8], [9], which captures perceived value as a price. In this paper, *we aim to explore this method for surveying and analyzing perceived value in relation to transformative robot sound.*

To explore our central research question, we conducted an investigation that leveraged prior work on transformative robot sound and incorporated the PSM as a means of measuring perceived value. We reviewed related work on transformative sound and pricing models in Section II before designing a study and associated analysis methods in Section III. Figure 1 summarizes the key result and Section IV presents the results in detail. We discuss these results, their implications on the usefulness of transformative robot sound and the PSM, the strengths and limitations of this work, and future work in Section V. The primary contributions of this work include *demonstrating a significant increase of value due to transformative robot sound, introducing the PSM questionnaire to HRI, and providing guidance on use of the PSM.*

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II. Related Work

A. The Effects of Transformative Robot Sound

Transformative robot sound research has shown a consistent perceptual and objective benefit to HRI in recent work. For example, participants walking near a Baxter robot found added transformative sound in the form of music to be more calming, gentle, soft, smooth, friendly, and pleasant than just consequential sound, the sound that naturally arises from the robot's operation [10]. A Magabot approaching participants with different transformative sound profiles led to changes in perceived anthropomorphism, animacy, likeability, intelligence, and safety [11], [12]. In cooperative localization tasks, a hidden robot using broadband and tonal sound increased accuracy, inference speed, perceived noticeability, and perceived localizability [13]. Finally, in our own study of five robots, adding transformative sound consistently increased perceived happiness, energy level, warmth, and competence across robot archetypes [1].

The suitability of transformative robot sound may impact its effectiveness in improving HRI [1]. "Musical" or musically-inspired transformative sound led to better perceptions of a robot than "harmonic" or "mechanical" transformative sounds [14]. Personalizing transformative robot sounds through interactive feedback may also improve the sound's effectiveness for individual users [15]. While these works have established the benefit of transformative sound, it is not yet clear what the implications of robot sound are from a commercial perspective. Thus, *we aimed to extend prior work by also measuring the perceived value of adding transformative sound to consumer robots*.

B. Measurement Instruments for Perceived Value

In HRI, measurement instruments for attitudinal constructs generally use bipolar Likert-style questions [16]. In marketing research, the PERceived VALue (PERVAL) survey offers this commonly accepted format in a 19-item questionnaire [17] and has been partially implemented in work in HRI [6]. However, the PERVAL questionnaire requires a predetermined price for the product in question. Thus, to avoid bias from priming participants with a particular dollar value, *we sought an instrument that would not unnecessarily predispose respondents to a given initial price.*

Pricing models offer an alternative approach by measuring *price* (i.e., the amount users will pay for a product), rather than *value* (i.e., the benefit that a user gains from a product). Indeed, price likely acts as a proxy for value as users make purchasing decisions based on this balance of price and value [18]. Marketing research has developed several methods for determining acceptable prices: market data, experiments, indirect surveys, and direct surveys. We identified surveys that were most appropriate for HRI work, as previous market data and experiments on perceived value have flaws for our purposes. Specifically, market data requires access to sales data and does not facilitate the investigation of new products or features, while experiments are resource-intensive and can predispose perceived prices [19].

Indirect surveys, such as the Gabor-Granger method, measure willingness-to-pay by asking successive yes-or-no questions at various price points, similar to a binary tree. A reversed cumulative distribution of the results shows declining willingness-to-pay as the price increases. However, survey designers may introduce bias through the price points provided in the survey and the method best suits pricing situations later in the product development cycle [18]. Other indirect methods include conjoint analysis, where participants effectively rank features according to perceived value, and discrete choice models, where participants choose between different product profiles with various features and price points [19]. These methods can provide greater flexibility and accuracy but require intensive design support and complex studies to simulate market conditions [18].

Direct surveys begin with the simple question: "What is the highest price you would be willing to pay for product X?" Similar to indirect surveys, the results form a willingness-to-pay distribution. More complex direct surveys, such as the PSM, can also account for factors such as perceived quality [18]. However, accuracy and validity remain a concern for direct survey methods [19]. Alternative models and regression techniques for the PSM, also known as extended PSM, may help alleviate these concerns while maintaining user-based price expectations [20]. Though popular in practical marketing research [18], the PSM has seen limited use in HCI and, to the authors' best knowledge, no use in HRI [8], [21]. Work in HCI has examined the PSM in the context of value-based software engineering, where participants were presented with a mobile software application and a simulation of its functionality [8], or evaluated a software product they were already familiar with [21]. In this paper, *we applied the PSM with both the traditional and extended analysis methods to evaluate the PSM's promise for HRI.*

III. Methods

A. Participants

We conducted a study on undergraduate students from the Oregon State University School of Psychological Science Subject Pool to determine whether participants would value a robot differently when a recording of the robot included transformative sound. Participants included 97 adults between 18 and 54 years of age ($M = 23.2$, $SD = 7.2$), with 69.1% women, 27.8% men, 2.1% non-binary people, and 1.0% transgender men. Participants mostly had no awareness (49.5%) or were generally aware (38.1%) of the TurtleBot 2 or similar products; few had either investigated (5.2%), participated in a demo of (5.2%), or regularly used (2.1%) such products. Few participants (19.6%) had educational, hobby, or work experience with music or other sound-related fields. All study procedures were approved by Oregon State University under protocol #IRB-2019-0172.

B. Hypotheses

We aimed to extend our past work by incorporating a new hypothesis while confirming prior results in [1]. Thus, we added the new hypothesis:

H1: Adding transformative sound to a robot will lead to higher perceived value of the robot and higher purchasing interest in the robot.

while maintaining the hypothesis in [1]:

H2: Adding transformative sound will lead to improved perceptions of robot valence, energy level, warmth, competence, and comfort.

C. Study Design

The study employed two videos of a TurtleBot 2 robot previously used in [1]:

- `OriginalSound-BehaviorC-Towards.mp4` (original sound stimulus)

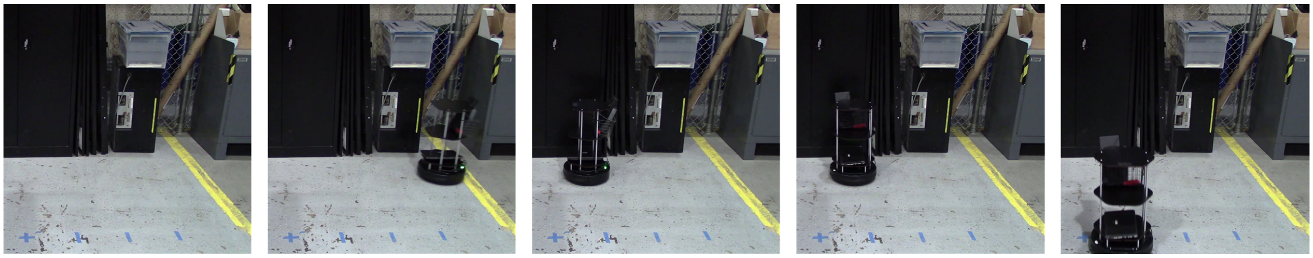

Fig. 2: Cropped keyframes from the video stimuli, which were 13 seconds long.

- `TransformedSound-BehaviorC-Towards.mp4` (transformed sound stimulus)

These videos are available in [22] and feature the TurtleBot 2 navigating a trajectory with and without overlaid transformative sound designed by a performing artist collaborator. Figure 2 shows keyframes of the video.

Using these videos, we developed a within-subjects study in which participants completed a 10-minute online survey. After providing informed consent, participants first completed an introductory module to calibrate their audio device volume. Participants then viewed one of the video stimuli, completed the value and social perception questionnaires, and completed an attention check. These steps were then repeated for the remaining stimulus. Stimulus order was counterbalanced across participants. In the final part of the experiment, participants completed a free-response question and demographic questionnaire. All measures are described in more detail in Sec. III-D.

Participants were compensated with course credit for completing the surveys. Participants who did not finish the survey (7), failed an attention check (1), or responded with "0" for any pricing questions (2) were excluded from analysis. No participants had previously participated in studies from [1].

D. Measures

The 10-minute survey included these questionnaires:

Value questionnaire: after each stimulus, van Westendorp's Price Sensitivity Meter (PSM) captured the price in USD for the robot shown in each clip relative to perceptions of the robot as *too cheap* (TC), *cheap* (C), *expensive* (E), and *too expensive* (TE) by asking [3]: "At what price would you...

- ...begin to think the item is so inexpensive that you would not buy it because it would be poor quality?" (TC)
- ...think the item is a bargain - a great buy for the money?" (C)
- ...think the item is getting expensive, but you still might consider it?" (E)
- ...begin to think the item is too expensive to consider?" (TE)

Participants were directed to indicate responses as whole numbers in USD. A five-item, unipolar Likert scale question also extracted *purchasing interest*. The wording of each question originated from Qualtrics [23].

Social perceptions questionnaire: after each stimulus, the Robotic Social Attributes Scale (RoSAS) captured participant perceptions of *warmth*, *competence*, and *discomfort* subscales by combining six component attributes for each subscale [24]. Participants rated each attribute on a six-point bipolar Likert scale from "definitely not associated" to "definitely associated." *Valence* and *energy level* from the circumplex model of affect were acquired via participant association of the robot with "happy" and "energetic." The "happy" item also contributed to the warmth subscale.

Free-response question: after both stimuli, a free-response question asked "[w]hat part(s) of the products stood out to you most or most strongly influenced your responses throughout the survey?"

Demographic questionnaire: a final questionnaire recorded participants' age, gender, ethnicity, nationality, hometown, profession, robotics experience, and musical experience.

E. Analysis

In this work, we focus on responses to the financial value and social perceptions questionnaires, which were evaluated for normality using Shapiro-Wilk tests. As all response groups were found to be non-normal with $p < 0.05$, responses were analyzed using Wilcoxon matched-pairs signed-rank tests with a significance level of $\alpha = 0.05$ [25]. To better control for Type I errors, we divided the measures into groups of price and purchasing interest for **H1** and social perceptions for **H2** and applied Holm-Bonferroni corrections to the Wilcoxon tests' resulting p-values [26]. We report the Wilcoxon test statistic W, the null hypothesis probability p, and the effect size as rank-biserial correlations r_{rb}. All statistical analyses were conducted using jamovi [27], [28].

Responses to the financial value questions were further analyzed through traditional and extended PSM analysis. In traditional PSM analysis, the four questions yield empirical cumulative distribution functions for *too cheap* ($Q_{TCh}(P)$), *cheap* ($Q_{Ch}(P)$), *expensive* ($Q_{Ex}(P)$), and *too expensive* ($Q_{TEx}(P)$) [20]. The reverse cumulative distribution functions of *too cheap* ($1 - Q_{TCh}(P)$) and *expensive* ($1 - Q_{Ex}(P)$) are plotted along with $Q_{Ch}(P)$ and $Q_{TEx}(P)$ to identify the intersections of interest:

- *Marginal cheapness*: $1 - Q_{TCh}(P) \cap Q_{Ch(P)}$
  The lower bound of the acceptable price range.
- *Marginal expensiveness*: $1 - Q_{Ex}(P) \cap Q_{TEx(P)}$
  The upper bound of the acceptable price range.
- *Indifference price*: $1 - Q_{Ex}(P) \cap Q_{Ch(P)}$
- *Optimal price*: $1 - Q_{TCh}(P) \cap Q_{TEx(P)}$

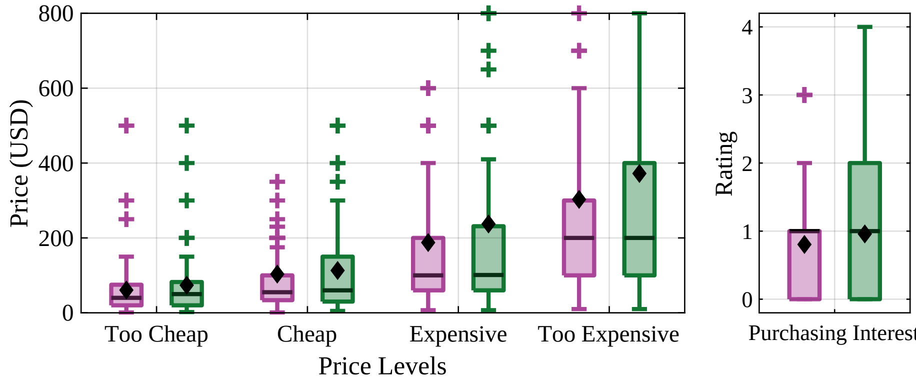

Fig. 3: Responses to the value questionnaire. Boxplots include boxes from the 25th to the 75th percentiles, **black lines** for medians, **black diamonds** for means, whiskers up to 1.5 times the inter-quartile range, and "+" marks to indicate outliers. *Original sound* stimulus responses in purple boxplots are placed to the left and *transformed sound* stimulus responses in green boxplots are placed to the right of each question gridline. Filled-in boxplot pairs indicate significant differences. The "Price (USD)" y-axis is truncated for legibility.

In extended PSM analysis, log-logistic distributions are regressively fit to $Q_{TCh(P)}$, $Q_{Ch(P)}$, $Q_{Ex(P)}$, and $Q_{TEx(P)}$. These models are used to find frequency distribution functions of interest:

- *Bargain price*: $F_B(P) = Q_{TCh}(P) - Q_{Ch}(P)$
- *Acceptable price*: $F_A(P) = Q_{Ch}(P) - Q_{Ex}(P)$
- *Premium price*: $F_P(P) = Q_{Ex}(P) - Q_{TEx}(P)$

The maximum of each function indicates the most likely price associated with the distribution, which may offer more precision when compared to traditional PSM analysis [20].

IV. Results

A. Statistical Analysis Results

Wilcoxon matched-pairs signed-rank tests with Holm-Bonferroni corrections for the five measures in **H1** showed that transformative sound led to significantly higher values of the *too cheap price* ($W = 256.5$, $p = 0.039$, $r_{rb} = 0.374$), *cheap price* ($W = 291.5$, $p = 0.012$, $r_{rb} = 0.504$), *expensive price* ($W = 397.5$, $p = 0.015$, $r_{rb} = 0.444$), *too expensive price* ($W = 267.0$, $p = 0.019$, $r_{rb} = 0.484$), and *purchasing interest* ($W = 50.5$, $p = 0.037$, $r_{rb} = 0.563$). Figure 3 shows the response distributions.

For the five social perceptions measures included in **H2**, Wilcoxon tests with Holm-Bonferroni corrections showed that transformative sound led to a significant increase in *energy level* ($W = 131.0$, $p < 0.001$, $r_{rb} = 0.866$), *valence* ($W = 0.0$, $p < 0.001$, $r_{rb} = 1.000$), *warmth* ($W = 170.0$, $p < 0.001$, $r_{rb} = 0.859$), and *competence* ($W = 1180.5$, $p = 0.024$, $r_{rb} = 0.289$). Transformative sound also significantly decreased *discomfort* ($W = 2644.5$, $p < 0.001$, $r_{rb} = 0.517$). Figure 4 shows the distributions of the social perceptions results.

B. PSM Analysis Results

Traditional PSM analysis, shown in Fig. 5, yielded identical values for the *marginal cheapness price* (50 USD), *optimal price* (100 USD), and *marginal expensiveness price* (150 USD) across sound conditions. However, *indifference price* was higher in the transformed sound condition (90 USD) than in the original sound condition (85 USD).

Extended PSM analysis found that adding transformative sound increased *bargain price* (+3 USD, from 44 to 47 USD), *optimal price* (+6 USD, from 83 to 89 USD), and *premium price* (+6 USD, from 148 to 154 USD), as shown in Fig. 6.

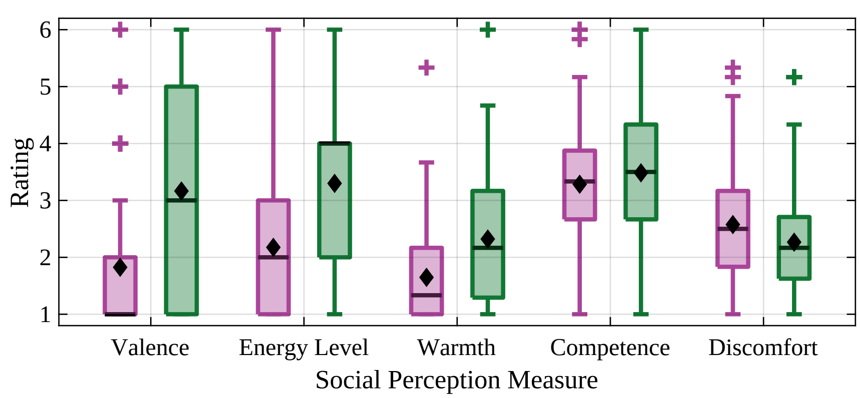

Fig. 4: Responses for the social perceptions questionnaire.

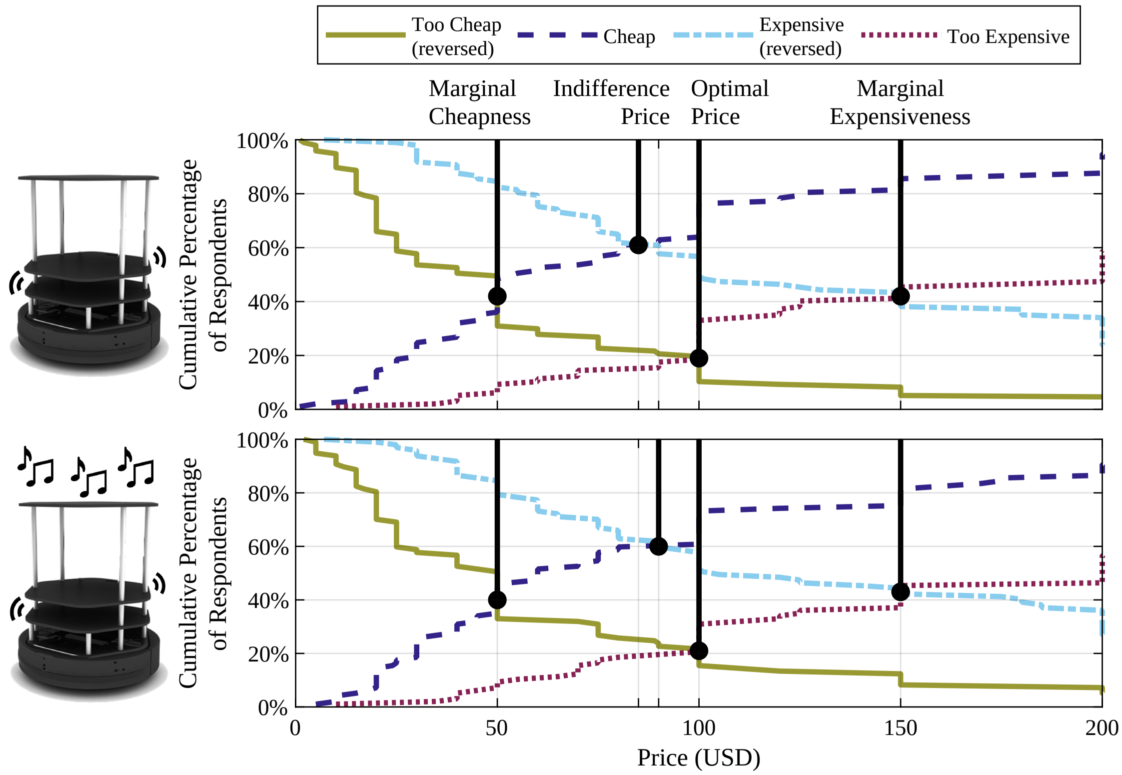

Fig. 5: Traditional PSM empirical cumulative distribution functions for the *original sound* stimulus (above) and the *transformed sound* stimulus (below). Vertical lines mark relevant intersections. The x-axis is truncated for legibility [29].

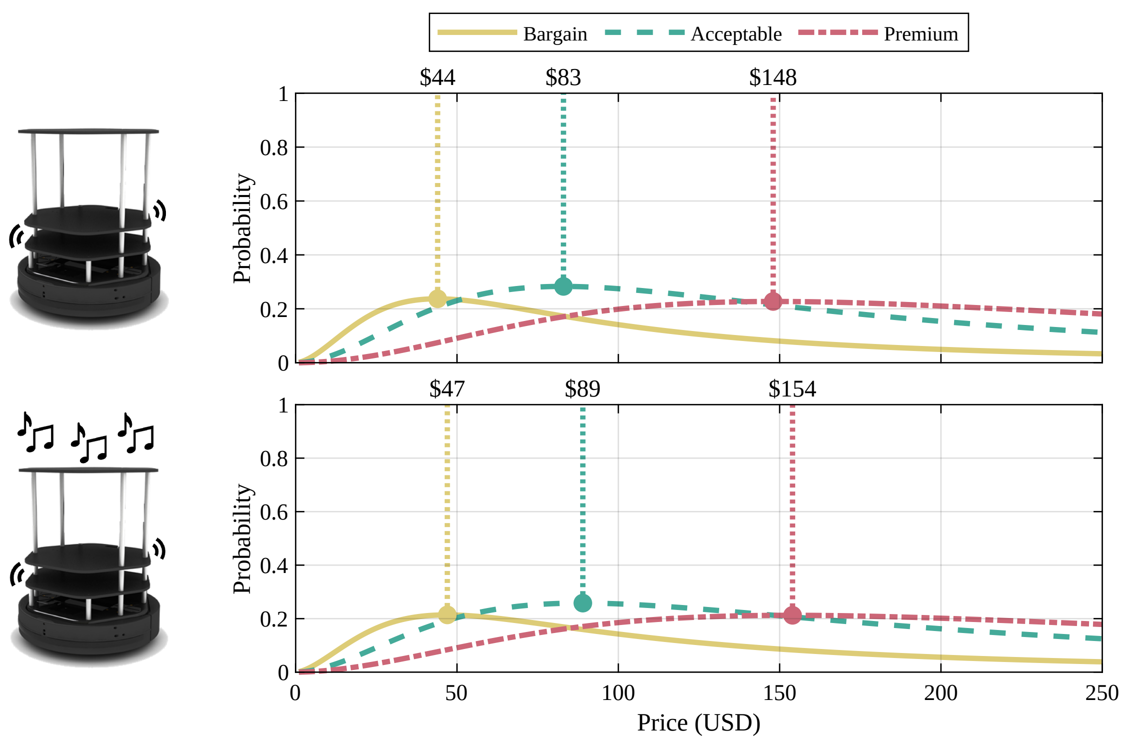

Fig. 6: Extended PSM regressively-fit frequency distribution functions for the *original sound* stimulus (above) and the *transformed sound* stimulus (below). Dotted lines intersect the maximum probability of each curve and mark the estimate associated with each line. The x-axis is truncated for legibility [29].

V. Discussion

Statistical, traditional PSM analysis, and extended PSM analysis all fully supported the expected responses for **H1**. At all requested price levels, participants indicated higher perceived value of robots with transformative sound. Extended PSM analysis produced an even clearer picture of the magnitude of perceived price differences. Transformative sound led to an increase of 3 USD for the *bargain price* (6.8%) and 6 USD for both the *acceptable price* (7.2%) and *premium price* (4.1%). The results corresponded closely with the *marginal cheapness*, *indifference price*, and *marginal expensiveness* as expected, since these points use the same pairings of distributions. *The extended PSM analysis method helped alleviate round number bias and the effect of high outliers* through its use of log-logistic regressions.

Social perceptions questionnaire results fully supported **H2** as well. In addition to replicating previously-recorded improvements to *energy level*, *valence*, *warmth*, and *competence* from [1], this work's analysis yielded an additional significant reduction in *discomfort*. This replication confirms and further validates the broad benefits of transformative robot sound.

A. Implications for Research Methods

Based on the overall pattern of results, we have a few suggestions for the use and analyses of the PSM. First, while the *acceptable price* frequency distribution function only requires the results of the *cheap* and *expensive* questions, the *too cheap* and *too expensive* questions may be important to account for an underlying assumption of *quality* [20]. As such, *we recommend including all four PSM questions*.

When evaluating robot features or comparing product profiles, PSM question responses should be tested for statistical significance, as the traditional and extended PSM analyses do not offer simple methods to determine significant differences. However, the extended PSM analysis may offer better insight into the magnitude of the difference between the distributions. In particular, when the direct responses do not yield normal distributions due to rounding bias, non-parametric statistical tests (such as the Wilcoxon matched-pair rank-sum test) and the traditional PSM analysis do not clearly specify the magnitude of a significant difference. Thus, *we recommend a combination approach of testing the direct responses for significance and using the extended PSM analysis to identify the magnitude of differences*.

A concern that may arise regarding the current study is the inaccuracy between perceived and actual retail pricing of the robot hardware, as the TurtleBot 2 is currently priced between 716 and 1185 USD [30], which far exceeds the values provided by participants. This mis-calibration is not wholly unexpected; marketing research has found previously that there are often issues when evaluating the value of complex and unfamiliar goods [19], especially when factors such as competitive effects are not readily available [18].

While these factors may be alleviated through different study designs, such as targeted sampling of intended customers or more comprehensive robot presentations, we argue that this discrepancy does not undercut the usefulness of the current approach. While the absolute values were obviously incorrect for the given hardware, as the measures here are *relative* comparisons, one might argue that any absolute pricing bias present in a given participants' ratings is constant across all of their judgments. Thus, this approach enables an estimation of how much transformative robot sound increased relative perceived value when compared to a non-transformative baseline, even in populations that might not have much experience with robots. These results highlight a potential strength of using the PSM in such HRI contexts and adeptly sidesteps the normal pitfalls and biases from sampling value solely from robotics researchers, who may value research platforms such as the TurtleBot 2 more highly than the average consumer. Therefore, *we do recommend using the PSM as a tool to compare the relative value of robot features*, as it enables quick and reliable identification of increased relative value reliably and quickly, even for populations that might not have a high degree of experience. This capability can help advance the implementation of HRI research on commercially-available robots.

However, robotics researchers and designers seeking accurate absolute price evaluations may consider modified procedures that better emulate market conditions, and provide a known target price for reference that might help constrain participants' estimations. Conjoint analysis and discrete choice analysis methods [18], [19] are also other options. It must be noted that these methods require significantly more effort, as they necessitate a wider range of product profiles in addition to more detailed information on the target market to derive accurate pricing information. Accordingly, *we recommend caution when using the PSM as a tool to evaluate the absolute value of a robot feature*.

B. Key Strengths & Limitations

The primary strength of this work lies in adapting a well established technique in marketing research and demonstrates, with statistical rigor, its effectiveness for application in HRI contexts. The work details and provides an example of extended analysis for the PSM, which allows a more detailed interpretation of the results. In addition, by successfully replicating prior work in transformative robot sound, this work also provides the opportunity to connect other psychological constructs to the construct of *value*. *Value* may serve as a useful high-level metric for HRI research, particularly when robots introduce both positives and negatives to users, and the PSM may serve as a useful instrument to measure value and tease apart these instances.

Limitations to this work include the online video-based survey format, which may not fully capture the effects of in-person HRI due to issues such as lack of embodiment and inconsistent audio or video playback. Also, the simple a-b comparison format using one form of transformative sound does not fully capture the entire potential sound design space, nor was it designed to. The goal of the current paper was to demonstrate a relationship between transformative sound and perceived value, which to date has not been demonstrated previously. However, adding additional sound profiles may lead to a more nuanced appreciation of what sound characteristics drive perceived value, which we aim to investigate in future work. Furthermore, the cultural context of the results is situated within that of the United States, and perceived value might change in other cultural contexts. In future work, we plan to deliberately recruit more diverse and representative participants.

C. Conclusions

In this work, we incorporated the PSM into an online survey and demonstrated that the addition of transformative robot sound not only produces benefits found in prior work, but also likewise provides a measurable increase in perceived value. Both traditional and extended analyses of the PSM confirmed this result. While estimates were not accurate when compared to the current retail prices of the featured robot, relative value comparisons still provided useful information as a comparative metric across robots viewed with transformative sound or not. Researchers and designers for HRI-centric robots, which have faced recent difficulties in achieving market viability, may benefit from the use of the PSM to identify valuable features. This work established that using the PSM to measure perceived value can help ensure robot features—like transformative robot sound—contribute to the overall value of robots.

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