Standardizing Reporting of Participant Compensation in HCI: A Systematic Literature Review and Recommendations for the Field

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ABSTRACT

The user study is a fundamental method used in HCI. In designing user studies, we often use compensation strategies to incentivize recruitment. However, compensation can also lead to ethical issues, such as coercion. The CHI community has yet to establish best practices for participant compensation. Through a systematic review of manuscripts at CHI and other associated publication venues, we found high levels of variation in the compensation strategies used within the community and how we report on this aspect of the study methods. A qualitative analysis of justifications offered for compensation sheds light into how some researchers are currently contextualizing this practice. This paper provides a description of current compensation strategies and information that can inform the design of compensation strategies in future studies. The findings may be helpful to generate productive discourse in the HCI community towards the development of best practices for participant compensation in user studies.

CCS CONCEPTS

• **General and reference → Surveys and overviews**; • **Human-centered computing → Empirical studies in HCI**.

KEYWORDS

meta-review, participant payment, HCI, CSCW, UBICOMP/IMWUT, UIST

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1 INTRODUCTION

The field of human-computer interaction (HCI) is a relatively young [10, 64] multidisciplinary field that focuses on the interaction between human end users and various technologies [21]. HCI draws most notably from computer science, cognitive science, and human factors engineering [83], yet continues to grow and evolve, incorporating components of various intersecting domains including social psychology [76], visualization [1], and library and information sciences [61]. The interdisciplinary nature of our field also means that our methods and the way we report our methods can vary greatly [8, 9]. We have seen increased attention in recent years at understanding ethical practices and the development of best practices within the HCI community [13, 30, 102]. One common but highly variable and ill-defined aspect of HCI methodology is participant compensation.

Compensation for human subjects research involves a series of inherently complex decisions. Research design, participant characteristics, regulations, availability of funds, and cultural norms may all factor in to compensation decisions [6]. Given the complexity of compensation decisions and study design, researchers have unsurprisingly highlighted inconsistencies in how scientists report on compensation in their manuscripts [55]. Inconsistencies in participant compensation and compensation reporting have been called out by numerous research communities as problematic [92]. These inconsistencies risk exacerbating current ethical and replicability issues in science [42] and is one facet that we could strengthen within our scientific community.

The role of the "user" or "participant" is integral to HCI. Across the various sub-disciplines, research is grounded in how user(s) interact with, engage, and utilize various technologies. Participants play a broad set of roles within user studies, including, for example, serving as stakeholders in design processes, providing insights and requirements to inform future design, and taking part in the collection or generation of data [100]. A search of just the CHI 2020 proceedings within the ACM Digital Library found that 87.4% contained the term "participant." While other domains like medicine, psychology and education have established best practices when it comes to compensation levels for certain types of participation or tasks, there still exists a high level of variability and calls for creating more standardized, ethical practices.

Within HCI, a majority of the compensation research has focused on aspects like comparing participant responses to micro-incentives [54, 69], new approaches to compensation [29], and motivation [82]. However, there are only a few examples of scholarship focused on analyzing the actual compensation levels, and those are focused within specific domains like micropayments [69]. Even with the critical role of the user within HCI research, there are not standard best practices for reporting on participant compensations nor how we report this process.

In this article, we report on a literature review for four of the major publication venues within HCI over 2018 and 2019 for research articles that employ user studies as part of their research methodology. Three key research questions motivated this research:

- How do HCI researchers provide context or justification for how they compensate research participants?
- What are the patterns for participant compensation within HCI scholarship?
- Are there standard processes for paying participants?

This research contributes the following to the CHI community: 1) a meta review of how HCI reports paying participants, 2) a qualitative analysis of justifications of participant compensations, which allow the community to learn from others in the field across the various disciplines and publication venues, and 3) recommendations on how to report participant payment. The goal of this paper is to outline current trends in participant compensation, present potentially useful rationales that have been used to justify previous compensation strategies, recommend a consistent compensation reporting structure, and to call for future research to evaluate compensation methods in HCI. What constitutes "ethical" or "appropriate" compensation varies across studies based on a range of contextual factors, of which many studies we analyzed did not include sufficient details (e.g., time commitment, geographic location). However, in this paper we take a stance that compensation should be reported on with sufficient details so that the equity of the compensation level can be evaluated and so that compensation decisions used within the community are transparent.

2 HOW DO WE DEFINE COMPENSATION LEVELS FOR RESEARCH PARTICIPATION?

In the United States, paying human subjects "became routine" in the early 20th century, including remuneration in the form of meals and transportation and even burial costs [59]. In one of the more notorious studies of its time, Dr. Walter Reed led an experiment in 1900 where Spanish immigrant workers were given $100 in gold and free medical care for a Yellow Fever experiment, in addition to another $100 if the participant contracted the disease [34]. Offering compensation to research participants is a common yet inconsistent practice in the United States, used to facilitate recruitment by incentivizing participation [38].

Research governing bodies usually provide guidance on what goes into compensation strategies. In the United States, the Institutional Review Board (IRB) is bound by regulations to review both the amount of payment and the proposed method and timing of compensation to assure that neither are coercive or present undue influence (21 CFR 50.20) [32]. Universities often provide overviews of participant compensation including general guidelines, international research, payment structures, and compensation of professionals [75, 95, 96]. Because of the high variation in research, there are not specific guidelines of exact levels or compensation schedules for researchers to consult during the design of their research.

Some fields with a long history of human-subject research have developed practices that may present useful lessons to the HCI community. The field of medicine has various documented practices and guidance that outline best practices for participant compensation. For example, The NIH Clinical Center reviewed multiple years worth of research studies and found that $20 for blood samples, $10 for a urine sample and $30 for a one-hour survey was average [26], which was validated through another independent survey of the field [84]. As with many other fields, there is also the potential for high variability in compensation; for example, MRIs ranged from $25 to $120, with variability even present in the same institution [23]. Another example of highly variable compensation occurred in a series of HIV cure studies, where participant compensation ranged from "no payment" to "nearly $2,000" [47]. Another literature review noted that variation was also found within the same research study, with a multi-site research study depicting a variation of $840 within it's own participants [39].

Psychology is another field with is a long history of compensating participants. Again, there is variability within this domain. However, there are organizations within psychology that give guidance on compensation levels for research participants. The NYU Department of Psychology guides that participants should be compensated between $10 and $20 per hour, and, in addition to monetary compensation, some studies offer food and/or free merchandise [74]. A common practice in psychology departments is recruiting heavily from the college/university community, especially undergraduates. Latterman and Merz found that out of 64 psychology studies they reviewed, 74% only involved course credit as the form of remuneration [57]. They also found a large range of compensation from $1 to $730, noting that increased monetary value equated to deeper involvement of the participant including multiple interactions, increased time, and invasive procedures. Like the medical studies, there are some standards across the literature for certain types of activities, like $15 for surveys, $25 for interviews and $445 for interventional studies [84]. A multiple regression analysis found that subjects were paid an average of $9.50/hour plus an additional $12 for each additional task involved in the study [57].

Within recent HCI literature, studies of participant compensation have focused almost solely on specific incentive structures and on the gig economy. Musthag et al. found that micro-incentive scheme had high variability and worked best for keeping research participants engaged in high-burden research initiatives [69]. Another form of alternative incentive is the "surprise" incentive and the underlying motivation for participation, especially if potential participants are surprised with a higher amount than initially expected [31]. Amazon Mechanical Turk (MTurk) provides an interesting platform for analysis, seeing the exponential growth in researchers using this platform for participant recruitment in recent years. Research into self-reported compensation levels of MTurkers find that $1 - $6 USD is the typical hourly wage [48, 62]. Hara et al.

conducted a task analysis and found that workers earned an hourly wage of approximately $2/hour, with only 4% of their sample earning more than the U.S. federal minimum wage of $7.25/hour [45]. Noted within Hara's research was the lack of reporting of demographics, including location, which would give further insights into the equity of the varying compensation levels based on minimum wages of the various locations of the participants. Follow-up work by this research team found there was a wage gap in that MTurkers in the U.S. on average earn $3.01/hour while those in India earn $1.41/hour [46]. The body of this discussion reinforces the assertions that, overall, MTurkers are underpaid for their contribution [50].

With such variation across domains with respect to participant remuneration, and no existing standards or best practices within the HCI domain, we found it imperative to assess how HCI researchers compensated research participants. Because of the interdisciplinary nature of HCI research, we also chose to review multiple venues of HCI research publication to ensure we had a representative collection including different sub-communities and research methods.

3 METHODS

We conducted a systematic literature review of all 2018-2019 manuscripts published in the Association of Computing Machinery (ACM) Digital Library associated with the Conference on Human Factors in Computing Systems (CHI), Conference on Computer Supported Cooperative Work (CSCW), Conference on Ubiquitous Computing (Ubicomp/IMWUT), and Symposium on User Interface Software and Technology (UIST) that included the search term "participant". We included these four venues because they represent the top four impact factor publication venues for HCI research. Additionally, they provide a nice variation of HCI-focused research. This resulted in an initial set of 2478 papers.

We used the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) approach to structure the evaluation of articles identified in the initial search [66] PRISMA focuses on ways in which authors can ensure a transparent and complete reporting of this type of research [42]. Each paper, including title, abstract, and text was reviewed by a member of the research team. Papers were excluded from the analysis if the study did not involve participant recruitment (such as observations in a public setting) or did not include a user study (such as literature reviews). Additionally, we set a criteria that only full papers would be analyzed which led to the removal of posters, late breaking work, and demos. We ended with a final collection of 1662 papers, describing 2250 unique user studies in the final data analysis. There are more unique user studies than research papers as some papers reported on several user studies. Figure 1 shows the process used that resulted in the final set of 1662 papers used for analysis.

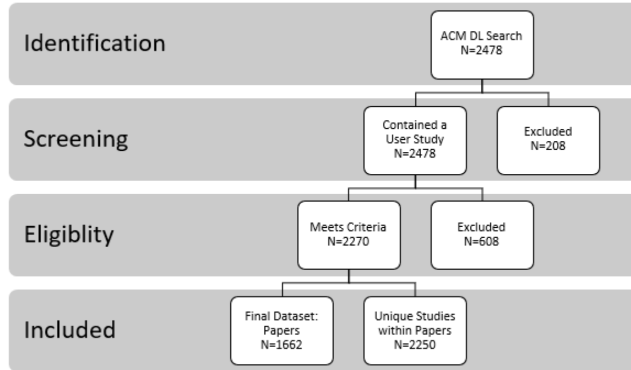

Figure 1: PRISMA Diagram

3.1 Categorical Data

As the research team reviewed each paper, we developed categories that allowed us to characterize and compare both the compensation and reporting. We manually extracted 17 categories which are listed in table 1. When a manuscript described multiple studies we separated these activities into distinct rows when the studies involved different participants, payment amounts, vehicles of payment, or payment structures. For all of the categories listed in Table 1, when a paper included no details about a category, we noted this as "unspecified." To complete these categories for the 2250 studies included in the review, papers were randomly and evenly distributed among the authors to review. The research team met weekly over a six month period to collectively review the data, address open questions, and discuss emerging themes.

The researchers used an iterative inductive analysis approach to develop common clusters. For this iterative analysis, the researchers first independently open coded the dataset, developing their own classifications. The team then met to review each classification schema, discuss differences, and develop a final set of classifications to be used for each of these categories. The final classifications are listed in Table 1. This qualitative data analysis allowed for a more standardized classification and reporting of the studies included in analysis.

3.2 Qualitative Assessment of Compensation Justifications/Rationales

Out of the 2250 user studies, 266 (11.8%) of the studies contained a specific rationale or justification for the compensation provided to participants. We captured the justification text in the metadata table and then ran a thematic analysis on this data. Three researchers met to review a subset of the justifications and create a initial codebook. Two researchers coded a subset of 75 justifications. The group met again to discuss codes they felt were missing and to discuss any remaining questions. The final code book with definitions can be found in Table 2. Two of the researchers took the code book and applied them to the entire dataset. There was an overall agreement of 96.9% with a Cohen's Kappa of 0.75, indicating substantial agreement between the two coders. A full breakdown of the analysis per code is located in Table 3.

3.3 Ethical Considerations

Within the results, we do not report exact dollar amounts associated with averages across the field. This is purposeful in that we do not believe it is appropriate for this research to be used as a justification for what the field *should* pay research participants. Rather, we aim

Table 1: List of data collected from each manuscript

	Metadata	Description
Manuscript Details	Publication venue	CHI, CSCW, Ubicomp/IMWUT, UIST
	Year published	2018 or 2019
	Title	Copied from manuscript
	Keywords	Copied from manuscript
Participant Details	No. of participants	Total number of participants recruited to participate (regardless of completion or later exclusion from data analysis)
	Type of participant engagement	Type of activity. Could include one or more of the following: Controlled tasks, deployment, diary, interview, observations, passive data collection, survey, workshop/focus group
	Location	Where the majority of the study activity took place. Could include one or more of the following: Participants' homes/field study, Lab, Online, Unspecified
	Type of participant	Description of inclusion criteria as stated in the manuscript
	Protected class	Participant groups identified as protected groups or vulnerable populations by U.S. Law and the Office for Human Research Protections. Includes pregnant women, people incarcerated, low SES, etc. (see text for full definition)
	Duration	Length of participation, in minutes, hours, days, weeks, or months depending on the study
	No. of sessions	Number of unique sessions a single participant would complete
Compensation Details	Compensation included	Did participants receive any compensation, gift, or reward? Yes/No
	Amount paid	Total amount of compensation provided to a participant
	Vehicle of payment	How was the compensation provided? (cash, gift card, movie ticket, etc.)
	Justification of payment	Did the authors provide reasoning for their selected compensation vehicle or amount? Yes/No
	Justification text	Reasoning for payment, copied from manuscript
	Payment structure	Common rules used for guiding compensation, such as payment provided per task completion or based on performance

to highlight trends found within the last several years. Appropriate compensation levels change based on temporal factors like inflation rates, current federal or state policy (e.g. minimum wage), where the research participant resides, where the research takes place, and the cultural values, to name a few. Therefore, we elected to focus on ranges of incentives present within the data, payment structures utilized, and the rationale or justifications given for the compensation levels, with the goal of informing the development of compensation strategies moving forward.

4 RESULTS

4.1 Reporting Compensation

Our first objective was to understand which aspects of compensation are reported or not reported within HCI literature. We looked at four primary factors regarding compensation: 1) if compensation was provided, 2) amount of compensation provided, 3) participation duration, and 4) mode of payment (e.g. gift cards, cash, movie tickets, etc.) [6].

We found that the majority of manuscripts did not report whether or not compensation was provided to study participants (N=1303, 57.9%). We identified only 70 studies (3.1%) that explicitly stated that participants were not compensated.

A small number of the manuscripts included a comment that compensation was provided, but did not provide any details. This included studies that noted participants received an "incentive" or "small compensation" without further information (N=88, 3.9%).

We also looked at the duration of participation, as the amount of time required of the participant can influence the compensation structure. We identified 762 manuscripts (33.9%) that did not report participation duration.

Finally, we looked for information on the mode of payment and found that 781 manuscripts (34.7%) did not provide information on how compensation was distributed.

Looking at these four factors collectively, and accounting for overlap in non-reporting within single studies, we found that **84.2% (n=1894) of studies did not report on at least one of these**

Table 2: Qualitative Code Book - Metadata

Code	Definition
$/task or activity	Compensation is defined by specific activities or tasks
$/time interval	Compensation is defined by specific intervals of time
No/lower levels of compensation	Includes comments about why no compensation was provided or why a lower level of compensation was provided
Difficult to access info	Includes comments about additional compensation because of the difficulty to access specific information
External source of influence	Mentions the influence of an external source like a funding source or community organization
Economically disadvantaged	Mentions that participants are low SES or economically disadvantaged
Expertise	Includes comments about compensation based on expertise or knowledge
Minimum wage	Mentions minimum wage
Food/refreshments	Includes providing participants with food or beverages
Specific scheme / payment structure	Includes rationale for varied payments that include task structures and bonuses
Competition/raffle	Mentions raffles or competition for specific levels of compensation
Transportation	Mentions compensation for transportation to/from research engagement
Assumption by researcher	Includes that researcher(s) made an assumption with respect to the compensation
Gratitude/appreciation	Mentions compensation was a "gift" or was in "appreciation" or with "gratitude"
Comparison to pilot study	Includes comparing current compensation level to that of a pilot study
Comparison to other research study	Includes comparing current compensation level to those of a previous study
Funding limitation/ barrier	Includes limitations to compensation levels based on funding barriers

Table 3: Qualitative Inter-Rater Reliability

Code	% agreement	Cohen's Kappa	Level of Agreement
Difficult to access info	100.00%	1.00	Perfect
Transportation	99.65%	0.95	Almost Perfect
Minimum wage	98.95%	0.93	Almost Perfect
Economically disadvantaged	99.65%	0.89	Almost Perfect
Food/refreshments	99.30%	0.89	Almost Perfect
Gratitude/appreciation	98.60%	0.85	Almost Perfect
Comparison to other research	97.55	0.82	Almost Perfect
Competition/raffle	97.2%	0.82	Almost Perfect
Expertise	98.95%	0.79	Substantial
No/lower levels of compensation	95.80%	0.72	Substantial
$/time interval	88.46%	0.71	Substantial
Specific scheme/payment structure	94.06%	0.69	Substantial
Funding limitation/barrier	99.65%	0.67	Substantial
Comparison to pilot study	97.90%	0.61	Substantial
$/task or activity	81.47%	0.60	Substantial
External source of influence	94.76%	0.54	Moderate
Assumption by researcher	94.41%	0.44	Moderate

factors (whether compensation was provided, the compensation amount, the mode of payment, or the participation duration), and thus did not provide sufficient details to understand their compensation structure.

4.1.1 Rationales/Justifications for Compensation. Reporting rationales for compensation decisions can be an important step in developing community practices. A primary goal of this paper is to provide an overview of existing rationales to support the design of future studies. Here, we present a thematic analysis of factors that influenced prior compensation strategies. We believe these may provide useful guidance for researchers as they make compensation decisions for future user studies.

A total of 286 (11.2%) of papers analyzed had a rationale or justification for the level of compensation. Through the qualitative analysis, we identified six factors that were frequently used to determine compensation levels. These factors include: compensation based on past studies or pilot studies, minimum wage, influences from organizations outside of the research team, participant expertise, existing compensation models, and lack of compensation. Table 4 highlights examples from the dataset of the various types of justifications and rationales. These rationales provide examples that have been used within the HCI scientific community in prior studies to make compensation decisions. By including them in the publications, these authors provide additional context for the reader that helps further ground the work, as well as provide key information to those wishing to replicate the research.

4.2 Compensation levels

Out of the 2250 individual studies we analyzed, 660 (29.3%) reported a monetary compensation to the research participants. The value of compensation ranged from $0.05 USD to $700.00. When taking into consideration participant time as a factor of the research participant, we can only report on 66.0% of these studies. Of those, the hourly compensation ranged from $2.86 to $240. When looking at this data by publication venue, we found moderate variations (see Table 5). *NOTE:* not all compensation was reported in USD. We converted all currencies into USD on 9/9/2020. While this is an imperfect practice, as exchange rates are a floating index, it gives some form of normalization, as not all studies reported exact dates/periods when the compensation took place.

We looked to see if compensation levels differed by publication venue. Table 5 shows the number of studies included in the analysis, the number of studies that provided compensation, if there was a mention of IRB or ethics committee review, and the monetary ranges. We also looked at the average hourly rate provided to participants. As illustrated in Figure 3, we found no significant difference in hourly compensation rate between venues ($F=.544$, $p=.695$).

We did find a significant correlation between hourly compensation and the primary location of the study ($F=2.815$, $p=.039$). Pairwise comparisons indicate that compensation was higher for studies that took place at participants' homes compared to online studies ($p=.022$) and lab studies ($p=.045$). Figure 4 shows illustrates this difference.

There were several compensation vehicles present in the dataset. Table 6 provides an overview of the most common modes of payment with the various ranges in value attached to each. Within the gift card/gift certificate category, Amazon was the most popular (41.1%). For those that gave an option, common vehicles included cash, gift cards, mobile credit, and class credit.

An overwhelming majority (61.0%) of these did not directly specify how participants received the noted monetary value. 85.4% of this subset provided a currency value or range of currency value but did not stipulate how that value was transferred to the research participant. For the remainder of the unspecified compensations, authors would report that participants were "compensated," "paid," or given "incentives," "monetary rewards," or "some compensation." Additionally, studies that utilize crowd source workers rarely specified that workers were compensated via the specific platform's compensation channel.

There was a variety in different types of studies. For the $/hour analysis, these were all studies that provided exact fixed times for specific types of participant engagement like taking a survey, providing an interview, or completing a task/experiment. However, field deployment is another type of research engagement where research participation can vary over a longer duration of time. A total of 237 (10.5%) have a duration of participation greater than one week (7 days). Monetary compensation ranged from $4.00 to $700.00 and were transferred to the participant via cash, Visa/Amex gift cards, non-specified gift cards, gift cards to specific establishments (Amazon, Tim Hortons, Target), bank transfers, and financial applications (e.g. PayPal). Non-monetary compensations included course credit, vouchers, movie tickets, mobile credits, technology (e.g. tablet, fitbit, pedometer), and food/beverage. "Gifts" and "tokens of appreciation" were also provided.

Finally, we looked at if and how compensation varied based on whether the study recruited participants who are classified as a protected class. Based on the legal definition of protected groups under U.S. Law [58] and vulnerable populations under the US Office for Human Research Protections [35], we defined a protected class as including Pregnant women, Neonates, Prisoners, Children, Individuals with physical disabilities, Individuals with mental disabilities or cognitive impairments, Economically disadvantaged, Socially disadvantaged, Terminally ill or very sick, Racial or ethnic minorities, and Institutionalized persons (for example, persons in correctional facilities, nursing homes or mental health facilities). We identified 332 (14.8%) studies that included a protected class as participants. Of these 332 studies, 109 (32.8%) provided compensation, 10 (3.0%) did not provide compensation, and 213 (64.2%) studies did not report on compensation. When comparing compensation between studies that included a protected class (N=109) and those that did not (N=768), we found that compensation was significantly higher for those that included at least one protected class ($t=2.02$, $p=.048$). Figure 4 illustrates this difference in compensation.

Table 4: Exemplar Compensation Rationales & Justifications

	Rationales/Justifications
Lack of Compensation	"According to the Bangladeshi custom, no compensation was given. However, the participants were offered light snacks and tea." [44] "In compliance with our IRB, we did not offer financial incentives to participate in the study, but we did provide lunch catered by local businesses." [24] "There was no monetary compensation for completing the survey. Instead, we offered a different kind of reward to participants designed to motivate them to take both the test of spatial skill and the questions about their gaming preferences seriously: an opportunity to find out what their primary motivations for gaming were and how well they performed on the spatial test compared to average U.S. adult performance."[104]
Using Pilot/ Previous Studies	"Based on piloting, we paid participants $2 for participation, for a target rate of $8/hour." [16] "We estimated the time needed for each microtask based on pilot studies and paid a fixed amount for each Human Intelligence Task (HIT) with the minimum wage of our location ($7.25 per hour)." [60] "Each participant was paid $0.05 USD, comparable to contemporary surveys in 2012, and this was held constant across all four surveys for consistency." [51] "In line with existing research that shows browsing history being valued at about the price of a Big Mac..." [7] "Each participant received $1.00 USD in compensation, which we calculated using the average times of a pilot study and the same hourly wage of Kim and Heer (2018)." [49]
Minimum Wage	"...Our participants could make up to INR 3000 over a period of 12 days, i.e., INR 250 per day on average. This is higher than both the NREGA minimum wage of INR 192 per day in Rajasthan [42] and the declared state minimum wage for semi-skilled work of INR 223 per day [13]." [12] "Each worker was limited to a single task, and paid $0.17 upon successful completion. After the completion of the study, we paid each worker a retrospective bonus of $0.40 in order to ensure workers earned at least minimum wage for their time." [93] "We followed the highest state-wide minimum wage in the US ($11.50/hour at time of our study). With an expected completion time of 20 minutes, we round up to a $4 compensation per task." [97] "All participants were ethically compensated at a rate consistent with an hourly wage of at least $10/hr (the U.S. federal minimum wage in 2018 was $7.25). More specifically, the payout was $2.00 per session, and with a typical completion time of 10 minutes, this yielded an hourly wage of $12/hr." [70]

	Rationales/Justifications
Influence of Organizations Outside of the Research Team	"At the suggestion of the OCDV [Office to Combat Domestic Violence], we provided refreshments and compensated each participant with $10 for their time." [37] "Finally, our funding agency, IMLS [Institute of Museum and Library Sciences], prompted us to pay participating families a US $75 cash incentive." [101] "Based on consultation with the NGOs [Non-Government Organizations] and our Institutional Review Board, we compensated each user 7 USD, which is roughly a day's minimum wage for a skilled worker." [79] "The ENDGBV [office to End Domestic and Gender-Based Violence] suggested this amount as being appropriate to cover the cost of transportation to and from the FJCs [Family Justice Centers]."[36] "Before we ran the study, three highly experienced Amazon Mechanical Turk workers critically reviewed the questionnaire to ensure the questions were accessible and that the proposed remuneration was fair. They were paid an agreed rate of $20 USD."[56]
Expertise	"We paid experts $75 for taking part in a 90-minute study, which is commensurate with their specialized skills."[99] "We chose this compensation level based on the amount of time it took the first author to analyze the same data (approximately 30 minutes), estimating that faculty are compensated at approximately $100/hour based on typical faculty salaries in the U.S."[2] "This rate of pay is commensurate with participants' specialized skill in using a screen reader, a necessary and hard-to-fulfill prerequisite for our study." [77] "The rationale for this amount was that our participants are economically disadvantaged, and we should generously compensate them for providing us with important insights that would otherwise be difficult to obtain." [102] "We provided incentives to sustain participation, especially for lower-income brackets...Participants were thus compensated 50 SGD (37 USD) for taking part in the online deliberation phase. They could also earn up to 30 additional SGD (22 USD) depending on their participation (for posting, reading, reacting)." [80]
Specific Compensation or Payment Models	"To derive the amount for compensation, we took the May 2017 average for service providers from our local area from the US Bureau of Labor and Statistics which equated to $13.30/hour. We estimated a range of time for participation at 2-2.5 hours for both the surveys and the interview. This estimate equated to $35." [78] "The retainer model automatically posts tasks to Mturk as needed, and continuously adjusts worker compensation based on demand (i.e. if the retainer is empty then compensation will be higher, if the retainer is full then compensation will be lower)." [77] "Those who join the study receive $750 for participating. The final amount of compensation varies depending on compliance levels, which is measured in terms of the average percentage of daily data streams collected from the participant. The minimum compliance percentage to earn the full amount is 80%. Furthermore, this amount is paid out in installments across the study period following a specific schedule with the goal of keeping people in the year-long study." [65]

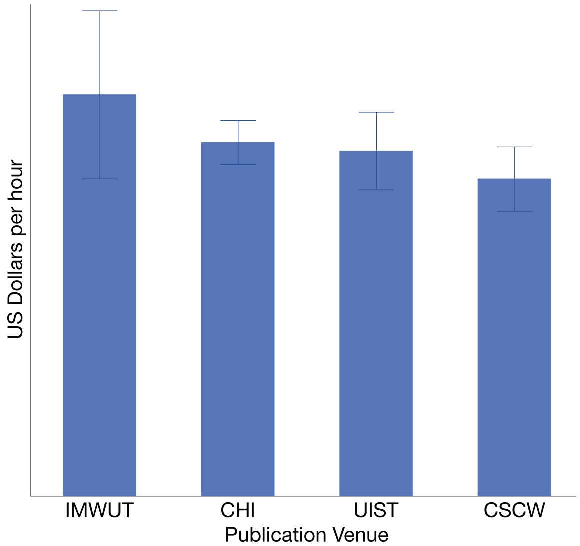

Figure 2: Compensation by publication venues, with standard error bars

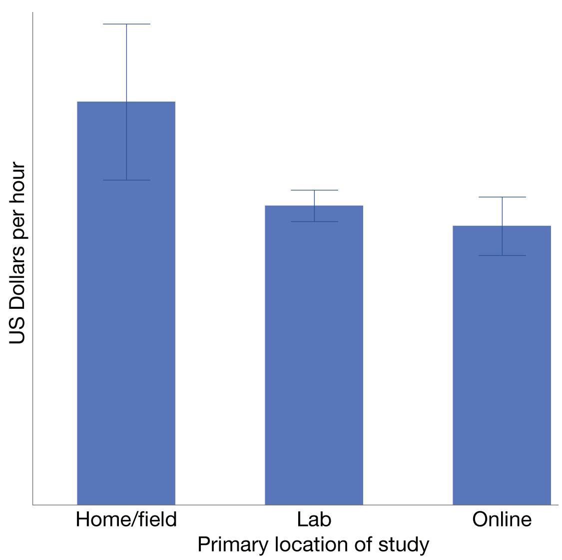

Figure 3: Compensation by study location, with standard error bars

4.3 Compensation Structures

Another key objective was to understand the different approaches to compensation, and the variables that were accounted for in the compensation methods. We identified nine different compensation structures. We describe these below and provide example citations for papers that fit these categories.

(1) **Fixed amount** - The most common compensation structure among the HCI manuscripts was provided a fixed amount to all participants regardless for how much time was taken for the given task or what was asked of the the participants [87, 108].

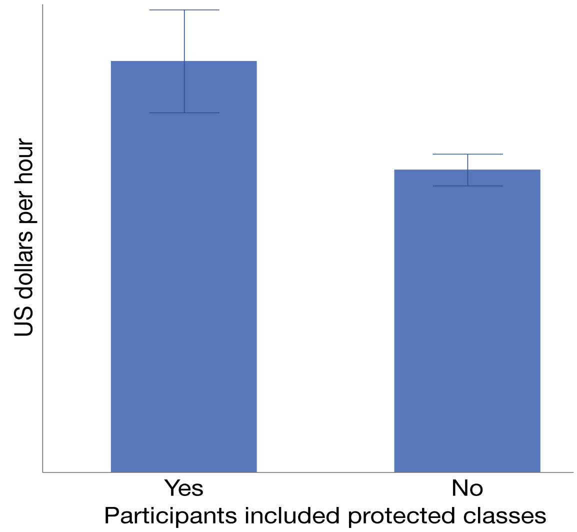

Figure 4: Compensation by Protected Class, with standard error bars

(2) **Amount per task** - We identified a high volume of manuscripts that provided a small, fixed amount of compensation for each task a participant completed. Tasks often consisted of short computer tasks, as is typical with Amazon Mechanical Turk studies. Alternatively, other studies provided fixed amounts for completing multiple surveys, participating in multiple interviews, or other in-person user study activities [22, 85].
(3) **Amount by time** - We identified a small set of manuscripts that provided participants with a fixed compensation per time period. This most often occurred in longitudinal studies, in which participants were compensated per day or week that they remained involved in the research [27, 105].
(4) **Varied by participant type** - Varying compensation amounts based on participant characteristics was another payment structure that emerged among the HCI studies. In some cases, studies compensated adults and children differently. Other studies varied compensation based on the country in which the study was occurring, though it was often unclear if these variations were driven by cultural factors or other reasons specific to geographic location [68, 94].
(5) **Varied by performance** - To incentivize optimal participation, a small number of studies offered compensation bonuses based on participants' performance of the study tasks. In most of these studies, the top N performers received an additional payment [11, 12].
(6) **Varied by participant expenses** - We found that a few studies noted that they compensated participants with a fixed amount and a variable amount based on participants' transportation expenses. While a less common payment structure, we feel this offers a nice model that researchers could consider in future studies [14, 43].
(7) **Participant's choice** - In a small number of studies, participants selected their preferred compensation. For example, student participants could choose between course credit or a monetary payment. We also found a few studies in which

Table 5: Compensation by Publication Venue

Parameter	CHI	CSCW	IMWUT	UIST	Total
Total # of User Studies	1470	360	236	184	2250
Provided Compensation	551 (37.5%)	172 (47.8%)	91 (38.6%)	63 (34.2%)	877 (39.0%)
IRB/Ethics Committee Review Mentioned	362 (24.6%)	136 (37.8%)	94 (39.8%)	19 (10.3%)	611 (27.2%)
Range in Monetary Compensation	$0.05 - $700.00	$0.10 - $180.00	$0.20 - $350.00	$1.25 - $90.00	$0.05 - $700.00
Range in Hourly Monetary Compensation	$3.00 - $240.00/hr	$2.86 - $104.17/hr	$3.33 - $200.00/hr	$6.66 - $100.00/hr	$2.86 - $240.00/hr

Table 6: Compensation Vehicles

Mode of Compensation	**Total N**	**Range in Value**
Unspecified/Assumed Cash	381	$0.14 - $350.00
Gift Cards/Certificates	180	$5.00 - $700.00
Crowd Work Platforms	176	$0.05 - $15.00
Unspecified/Not Noted	56	Not Reported
Voucher	49	$3.60 - $75.00
Cash/Local Currency	35	$5.00 - $75.00
Class Credit/Extra Credit	16	N/A
Food/Beverage	11	N/A
Option Between Various Modes	11	Not Reported - $30.00
Gifts, Unspecified	10	Not Reported - $25.00
Technology	9	Various Types (tablet/fitbit/pedometer - $50.00 value)
Movie Tickets	7	Not Reported
Qualtrics Credits	3	Not Reported
Donation	2	Not Reported
Mobile Phone Credits	2	Not Reported
Shoes	1	Not Reported
Medical Care	1	Not Reported
Free Admission	1	Not Reported

participants could select between volunteering or receiving remuneration. [81, 103]

(8) **Donation** - Another less common but interesting payment structure was pledging donations to charity for participation. Often the charities were directly aligned with the research topic, such as a national disease foundation when recruiting participants with that particular diagnosis. [67, 106]

(9) **Negative reinforcement/penalties** - In the final payment structure we identified, researchers used penalties within their compensation structure. This meant that participants could lose a small portion of their compensation for poor performance or inactivity. [17, 65]

Notably, studies often included combinations of these compensation structures. Many studies included a fixed minimum that all participants would receive and then include bonus incentives for completing more tasks or for high performance. In other studies, for example, researchers provided participants with the option to select between a fixed payment amount or a donation to a charity.

5 DISCUSSION

This paper presents a comprehensive overview of compensation reporting and methods within HCI literature over a two-year period. Compensation methods are complex decisions, in which researchers must consider the benefits and potential ethical challenges of compensating participants. To support these decisions in future studies, we have presented a comprehensive list of factors reported to studies that detailed their justifications for their compensation decisions. Reflecting on existing practices, we propose a number of recommendations to the community, including the consistent reporting of compensation decisions and rationales.

5.1 Standardizing the Reporting of Compensation in User Studies

In reviewing HCI literature, we found the majority of papers do not report any details on compensation. Gathering data on compensation was challenging, as there is no standard for reporting compensation, leading to a lack of reporting and inconsistencies in how compensation is reported. Some metadata were commonly reported, such as participant numbers and characteristics of the participant pool. However, many important data were frequently not reported, including compensation amounts, or even if participants were compensated at all. The amount of time participants were engaged in the study and where the research took place were also not frequently reported. This makes it impossible to determine with any certainty what the norms are for participant compensation in HCI research.

The lack of reporting is a concern for the community when it comes to replicability of our research. Replicability has garnered much attention both within scientific communities and media in recent years [5, 18, 72]. The nature of HCI studies – e.g. studying context specific phenomena, engaging specific populations – weakens, if not eliminates, the ability for studies to be replicated exactly. However, compensation (generally) has been highlighted as one aspect of scientific methods that is under reported but important for addressing ethical and replicability issues in science [53].

Reporting compensation when using crowdsourced labor marketplaces like Crowdflower or Amazon Mechanical Turk is also a point of concern for several reasons, primarily because of the historical exploitation of this labor force [62]. Leading HCI researchers working in this space have explicitly asked researchers to stop citing their past work as a way to justify the continued underpayment of crowdsourced workers [89]. It has been noted that these workers often provide significant degrees of subject matter expertise, yet usually earn less than the legal minimum wages, have no health benefits, and can be summarily fired for any-to-no reason [40]. While we have seen calls from the community have discussed paying crowdworkers an ethical amount or at least minimum wage [88], there are still still studies taking place within HCI that pay crowdsourced workers well under documented minimum wages.

Improving standards for reporting participant compensation would increase transparency, facilitating a better common understanding of appropriate, ethical compensation. To that end, **we recommend that authors report the following components of participant compensation: the amount and form of payment, how long participants were engaged, and where the research took place.**

5.2 Factors to Consider in Compensation Decisions

A contribution of this work is an evaluation of compensation design rationales. While a small percentage of papers offered a thorough description of their compensation decisions, these explanations also offer useful considerations that may be beneficial in the design of future studies. Our review of rationales revealed that the most frequent rationales focused on how participants were paid by the task or factors that lead into why a participant was recruited in the first place (e.g. economically disadvantaged, or providing a subject matter expertise that is desired or required). The list of rationales provided in Table 2 should not be seen as a definitive list, but a reference point to start when thinking about justifying a compensation strategy. Due to the interdisciplinary nature of our field, this list could easily be expanded with additional representation of communities like Designing Interactive Systems (DIS) or Intelligent User Interfaces (IUI), or any other publication venue not selected for this analysis. By providing a rationale, the authors not only give the readers more confidence in the thought and consideration that went into the design of the compensation strategy, but also provide a way to teach the next generation of research scientists about the nuance and design that go into the various compensation strategies.**We recommend that authors include justifications or rationales for compensation decisions**. This was a motivation for including Table 4 and we encourage readers to use this as a reference point for considering possible factors in the decision making process and exemplars of how our community has reported on these past decisions.

5.2.1 The Importance of Cultural Contexts. Another key factor that should be taken into consideration when determining participant payments are the local variations in compensation with regards to customs and what is considered a living or minimum wage. This was a primary consideration in our decision to not report out on average payments but to provide a range. It would be impossible to provide a non-biased recommended per/hour participant rate for the many reasons that have previously been discussed. Additionally, we included a variety of best practices from non-U.S. and European studies. For example, in the justifications for minimum wage, we made sure to highlight examples from research settings in rural India, crowd workers from multiple countries, and U.S.-based participants. Additionally, we highlighted justifications that took cultural and regional contexts within other categories like influences of organizations outside of the research team, expertise, and in non-monetary compensations which included food and beverages. We believe that encouraging a standardization in reporting practices which would give more transparency and allow for readers and reviewers to make more informed decisions with regards to the fairness of the compensation is the most practical and unbiased path forward.

5.3 The Pros and Cons of Direct Compensation to Research Participants

While we primarily report on details related to studies that did compensate participants, we recognize that there are many cases in which compensating participants for their involvement in research would be inappropriate. Per the FDA's guidance document for clinical research, providing incentive payments for research can, without careful consideration, tip the scales ethically and limit the ability for participants to voluntarily offer consent [33]. As such, there is ethical precedent for not compensating research subjects, due in part to the potential for incentives to create bias in studies, especially when the impact of the amount or vehicle of compensation is not considered. Any payment to an individual in a study could engender positive feelings that colludes feedback and leads to false or overly-optimistic outcomes.

Lack of compensation can be somewhat standard within certain fields or settings, such as health care. One study mentioned that the direct compensation of clinician participants was not allowable per the IRB [78]. We also noted an example in our dataset of compensation being declined by clinicians who stated they would rather the funding be spent on further research and development [52]. While some clinical research trials compensate participants quite well, there are high levels of "volunteering" that takes place within these trials. This type of participation is often characterized as having additional meaning to the participant because of a personal interest in science, altruistic overtures of contributing to improvements of medical care, or supporting specific diseases or illnesses that are meaningful due to a personal or shared experience [15].

The practice of not compensating research participants monetarily is also quite common within research that recruits from colleges and universities. Within our own dataset, we found many instances of students not being compensated or where compensation was defined as credit (or extra credit) for the class where the research took place.

Overall, the ethical issues associated with compensation are complex and often dependent on specific factors unique to a certain study. There can be no blanket statement made regarding what constitutes ethical compensation, other than that it must be carefully considered on an individual basis. IRBs often facilitate this process via establishing compensation policies specific to their institution and/or reviewing and approving researchers' proposed compensation structure. This represents a critical step in the research process that was reported relatively rarely in our dataset–slightly over a quarter of the papers we reviewed mentioned an IRB or other ethics review, and far fewer mentioned this in relation to compensation or lack thereof.

Providing more transparency related to these types of decisions will both facilitate greater replicability as well as provide greater clarity on general standards and practices in the broad, evolving field of HCI. Given the strong connection between compensation methods and ethical research practices, we believe **there will be many cases in which researchers opt not to compensate participation, whether on an individual or institutional policy basis. Such decisions should be normalized within the community and reported within study manuscripts.**

5.4 Trends Across the Venues

The data presented in the previous section highlights several interesting trends. At the outset of this research, it was thought that several of the venues might share similarities since there is some overlap between the venues and the types of research that are presented. When one looks at the metric of participants were provided compensation, all of the venues were in a similar range (34-41%). This convergence highlights the consistency across the HCI venues. However, this raises questions regarding the levels of research where there is lack of compensation (voluntary) or the more common lack of reporting compensation in the field. One way to address the lack of reporting is to enhance the reviewing process. While training individual reviewers on what to look for when reporting compensation is possible, there are other, less resource intensive ways to provide guidance. To that point, **we recommend a best practice guide for new reviewers could be produced by each venue or the SIG itself, or guidance could be provided to the Associate Chairs (ACs) during the review process.**

Another trend observed was the variability in the various types of compensation vehicles reported. Again, this is an area where authors could be more transparent in how participants are paid. As noted, 61% did not directly specify how participants received monetary values. For those that did specify, gift cards/certificates were the most popular, with 41% of those being specifically for Amazon. For the class credit that was denoted, there were no monetary values established for this compensation. This is important because not all colleges/universities have the same monetary value attached to one course credit. For studies to be replicated or evaluated for ethical practices or fairness, greater context is needed in HCI study methods sections, especially with respect to the vehicles used to provide compensation to study participants. A surprisingly low number of studies mentioned any type of review by an ethics review board or committee. CHI, CSCW, and UBICOMP/IMWUT were in similar ranges (25-39%) while UIST stood out as an outlier (10%). While the number of studies that were actually received an ethics review was likely much higher, it was not a standard to report on this metric in research where a user study was utilized as part of the research methodology. The U.S. Office of Human Research Protections clearly articulates the need for institutional review when human subjects are involved [73], so the lack of documentation points to inconsistency in fullness of reporting methods. Again, this could be addressed during review processes or during training within our individual university and industry programs and culture.

6 OPPORTUNITIES FOR FUTURE WORK

In addition to the recommendations provided above, we also see gaps within HCI research to evaluate the effects of these compensation methods. Below we outline two possible paths forward to address these gaps.

6.1 Involving Participants in Compensation Decisions

In our analysis of payment structures and justifications, we noted that several studies either gave participants choices related to their compensation or involved relevant stakeholders during study design to determine compensation vehicle or amount. For example, Lascau et al. [56], who paid their participants (Amazon Mechanical Turk workers) a rate that worked out to approximately $16 per hour, engaged several experienced Turkers directly to establish a compensation rate validated by representatives of the community.

Similarly, Stähli et al. utilized "subject matter experts" in a prestudy to aid in the design of their main study; their compensation consisted of a drawing for one of three prizes (headphones and two different vouchers), which were selected with the help of these subject matter experts who, like the main participants, were pilots [91]. In asking what type of prizes to give out, the researchers may have gained insight they did not have previously toward which gifts would be of particular use to someone in this field.

Nanavati et al. described the importance of ensuring their communities of study received "tangible, desired benefits" from their fieldwork, including "using participatory methods during technology development; leaving the technology and simple documentation with multiple school affiliates; leaving the computers virus-free and with anti-virus software; and generally making ourselves available to help with any queries during and after the fieldwork" [71].

Additionally, some studies noted differing compensation vehicles across participants [3, 19, 25, 28, 63, 86, 98, 103, 107]. However, these studies did not report whether the choices of compensation vehicles were derived from the participants or if they were determined by the researchers, IRB, or some other external factor. Providing more clarity with regard to these types of differences in payment structure provides a basis for other researchers to make similar decisions in their own related work. Our analysis of the rationales provided in this dataset provide critical information across a range of factors that could be used by the HCI community in future work.

Without knowing it or not, the mode of compensation is often implicitly biased. A common form of payment is an Amazon gift card. It is assumed that because Amazon is a virtual marketplace, this form of payment would be beneficial to all participants. However, what this doesn't take into consideration is the participant's orientation to Amazon. It is possible that the participant does not support the company, and thus the compensation has less value to them than another participant that does not have that orientation. By adding in a more action-oriented approach of asking the participant *how* they want to be compensated, the community could further reduce implicit biases and share a small power dynamic with the participant. Therefore, another recommendation includes: **We contend that involving participants more meaningfully into compensation decisions warrants further attention within the HCI community.** Given the increased use of participatory and action research methods within HCI studies [20, 90], we believe there are under-explored ways in which we can involve communities, organization, and participants in these complex decisions that provides them greater voice in these important methodological decisions.

6.2 Evaluating Compensation Methods

In addition to finding overall low reporting of compensation strategies, we also found very few studies that evaluated how compensation influenced participants or study objectives. Notably, one study [41] did ask participants their perspectives on the compensation in an exit survey, while another study looked at how a "a loss aversion incentive protocol" influenced behavior [4]. **We see a clear opportunity for HCI research that focuses on compensation evaluation methods**. Numerous questions have yet to be explored in our field, such as: *How are different incentive structures viewed by various communities? When do compensations become coercive in user studies?* and *How do different method variables influence enrollment and performance?* While we may be able to draw from research in other fields, HCI researchers are well positioned to explore the influence of compensation on methods that are well-established and consistently used within the community, such as user-centered and participatory design sessions, online and laboratory experiments of novel interfaces, and technology deployments.

7 LIMITATIONS

This research is limited by the sample of papers we chose for analysis. We sampled a subset of the HCI community: CHI, CSCW, IMWUT, and UIST. Though these four conference proceedings constitute a significant proportion of HCI research, the list is not exhaustive. Additionally, our sample is a snapshot of these proceedings covering two years (2018-2019). It is possible that there are meaningful changes in both compensation and how compensation is reported over time, which would cause bias in our results. Future work could investigate longitudinal changes in compensation. For example, COVID-19 may affect compensation structures; future work might explore how compensation changes as more research is conducted remotely.

It was not possible to automatically extract data in the analysis of this paper, as there is no standardized method for reporting participants and compensation. All data used in this analysis were generated manually, which could introduce errors. As reported, there was strong agreement across the coders indicated via the inter-rater reliability intervals.

An additional limitation of this research is that it relies on self-reported data [9]. Paper authors described their own payments, participants, and methods. This likely introduces some inaccuracies into the analysis. As Caine et al. points out, there is likely some inconsistency between different authors' and communities' definitions of various methods. For example, a study that might be referred to as an ethnography in HCI, might not be accepted as an ethnography in anthropology [9].

8 CONCLUSION

The systematic review presented in this paper describes current participant compensation practices within the field of HCI. After reviewing 2250 unique user studies, found within 1662 manuscripts, we have synthesized and categorized current approaches to offering participant remuneration and the associated justification for paying or not paying study subjects. The findings presented in this manuscript may inspire HCI research scientists as they design user studies to develop a comprehensive plan for their compensation strategy and include their strategy in study dissemination artifacts. Key components of describing a compensation strategy include: what considerations went into the calculation of payment amount, how the compensation was transferred to the participant, and any contextual details that will give the reader a deeper understanding of this process and decision making. Normalizing the practice of reporting compensation will further strengthen evolving methodological standards and ethical practices in research design within the field of HCI.

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